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How Did the Financial Crisis Alter the Correlations of U.S. Yield Spreads?*

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Abstract

We investigate the pairwise correlations of 11 U.S. fixed income yield spreads over a sample that includes the Great Financial Crisis of 2007-2009. Using cross-sectional methods and non-parametric bootstrap breakpoint tests, we characterize the crisis as a period in which pairwise correlations between yield spreads were systematically and significantly altered in the sense that spreads comoved with one another much more than in normal times. We find evidence that, for almost half of the 55 pairs under investigation, the crisis has left spreads much more correlated than they were previously. This evidence is particularly strong for liquidity- and default-risk-related spreads, long-term spreads, and the spreads that were most likely directly affected by policy interventions.

Keywords: yield spreads; correlations; breakpoint tests; nonparametric bootstrap; credit risk; liquidity risk.

JEL codes: E40, E52, C23.

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1. Introduction

A persistent state of turmoil engulfed the international financial markets – particularly U.S. equity, debt, credit, and derivatives markets – between the summer of 2007 and the late spring of 2009. A number of papers (e.g., Caprio et al., 2010; Galí, 2010) have labeled such a state, characterized by unsettled and dysfunctional markets, as the "Great Financial Crisis." There is now little doubt that the Great Financial Crisis ravaged U.S. fixed income (debt and credit) markets in unprecedented ways (see Dwyer and Tkac, 2009). Using data from the epicenter of the crisis, a range of U.S. fixed income markets, we pose two questions. First, can the Great Financial Crisis be truly seen as an approximately 2-year crisis episode that progressively abated to leave markets in a "normal" state similar to the one that had prevailed before 2007? Or second, to the contrary, was the Great Financial Crisis so pervasive that it left the relationships among different fixed income segments permanently altered?

More generally, some economic literature has investigated the fabric that turns a state of turmoil in the fixed income market into a persistent regime so severe to merit being dubbed a crisis, or even a "great" one nonetheless. A number of papers have focused on anomalies in the univariate dynamics of the first (the level) and second (the volatility) moments of yield spreads, constructed as the difference between the yield to maturity of a riskier asset and the yield of a comparatively less risky (or riskless) asset (see, e.g., Guidolin and Tam, 2010; Muir, 2013), sometimes also using event studies (see, e.g., Nippani and Smith, 2010). However, a multivariate approach focused on the comovement (e.g., correlation) patterns across fixed income markets should also contribute to a useful economic characterization of the Great Financial Crisis. For instance, in a rare example of multivariate analysis, Dungey et al. (2010) develop a method based on structural identification via heteroskedasticity to separate market contagion from hypersensitivity during crises. They exploit the ability of multivariate generalized autoregressive conditional heteroskedasticity (GARCH) models to forecast the dynamics of correlations. However, their application concerns only the 1997-98 Asian crisis.

Another strand of the literature has intensely debated the exact dating of the Great Financial Crisis. The differing conclusions have often reflected the priors of the different researchers as well as their specific methodological approaches. With a few exceptions (e.g., Campbell et al., 2011; Frank and Hesse, 2009), most papers have agreed on early August 2007 as a potential starting date of the Great Financial Crisis, even though only a few have traced this claim back to the actual behavior of financial data. Moreover, only a handful of papers have ventured into establishing an end date for the Great Financial Crisis (see, e.g., Aït-Sahalia et al., 2009; Campbell et al., 2011; Guidolin and Tam, 2010). Usually such attempts have consisted of generic and informal claims about the possibility that the effects of the crisis were reabsorbed around mid-2009. In this paper, we develop a characterization of the Great Financial Crisis based on the multivariate behavior of a large set of fixed income yield spreads that offers a novel perspective on the end of the Great Financial Crisis.

Yield spreads measure various dimensions of risk. While studying the level of yields per se has value in certain contexts, many papers and articles in the literature favor the analysis of yield spreads because they offer a clearer picture of the underlying trade-offs for investors. We focus on fixed income yield spreads for several reasons. First, filtering a financial crisis through the lenses of spread data is an implicit way to relate financial events to the business cycle (see, e.g., Gilchrist et al., 2009). In general, yield spreads are likely to be informative of the channels through which financial prices affect the real side of the economy. In particular, fixed income spreads tend to widen shortly before the onset of recessions and to narrow again before recoveries. Analyzing the behavior and the common dynamics of yield spreads based on interest rates derived from the core of the financial crisis (i.e., fixed income markets) sheds light on some important aspects of the turmoil and on the relationship between economic activity and the evolution of fixed income markets. Second, economists are generally interested in understanding the mechanisms that link variables in a given market. The extent of comovement between fixed income yield spreads may have consequences for the cost of borrowing, the portfolio diversification strategy of investors of various types, and the modelling and forecasting of interest rates in the market under investigation. Moreover, a good understanding of the dynamics of credit and liquidity risk premia incorporated in the prices of fixed income securities potentially has a number of practical implications for portfolio managers and policymakers. On the one hand, through such understanding, financial market regulators may be able to improve capital allocation functions and the information aggregation process in fixed income markets. Furthermore, they may be able to evaluate the robustness of such markets to shocks to the financial system. On the other hand, investors may want to look at the dynamics of credit and liquidity risk premia to derive better information about the return and diversification properties of major asset classes. Overall, a careful assessment of the main characteristics of such premia may be associated with better investment and policy decisions over the business cycle.

Given these premises and objectives, we systematically investigate the empirical behavior of pairwise correlations between 11 U.S. fixed income spreads over a sample of weekly data between 2002 and 2011. These spreads are distinct in terms of the securities or markets to which they refer, the maturity of the underlying securities, and whether they were affected by specific policy measures by the Federal Reserve and policymakers more generally (e.g., the Treasury and the Federal Deposit Insurance Corporation) in reaction to the Great Financial Crisis. Our series measure yield spreads for a variety of instruments and markets, namely, 3-month London interbank offered rate (LIBOR) unsecured deposits, 3-month unsecured financial and asset-backed commercial paper (ABCP), 5-year swaps, 5-year Resolution Funding Corporation (REFCorp) strips, 5-year commercial private-label commercial mortgage-backed securities (CMBS), 10-year off-the-run Treasury securities, 20-year Moody's Baa-rated and Aaa-rated corporate bonds, 20-year Moody's Bbb-rated and Aa corporate bonds, and 30-year conventional fixed-rate mortgage-backed securities (MBS). This list also includes two typical mortgage-related risk premia because the U.S. mortgage market is identified as the catalyst of the financial crisis (see Frank and Hesse, 2009).[1]

We use a mixture of cross-section econometric methods to test the existence of nonzero correlations for groups of spreads and test for breaks in the correlations between spreads. We generally reject both the null hypothesis of no cross-section correlation between spreads in all subperiods we consider and the null hypothesis of constant pairwise correlations over time. We provide a characterization of the Great Financial Crisis as a period during which pairwise correlations between yield spreads were systematically and significantly altered, with spreads comoving with one another much more strongly than in "normal" times. Our work is consistent with the intuition that the Great Financial Crisis was a period of structural and systematic alteration of correlations between spreads, possibly (but not exclusively) induced by a soaring exposure of the underlying securities to common crisis factors (such as declining "risk appetite," liquidity shortages, and funding problems for intermediaries; see Brunnermeier and Pedersen, 2009). Implicitly, we consider the possibility that unconditional average correlations may be unstable over time. Although it is well known that rich but stationary models may be applied to describe the time variation of conditional correlations, we identify and interpret medium-term movements in average correlations across pre- and post-crises regimes.[2]

Our results are considerably more intriguing than just a novel characterization of the Great Financial Crisis as a shock wave that has affected spread correlations in addition to their means and volatilities. Using nonparametric bootstrap methods, we find evidence that the Great Financial Crisis has left the spreads much more correlated than before the crisis. This evidence appears to be particularly strong for three (occasionally overlapping, but clearly defined) subsets of spread pairs, defined according to spread features – that is, characterized by liquidity problems, measuring default risk, or directly influenced by policy interventions. We also discuss which factors might have driven the correlations during and after the Great Financial Crisis. First, we find that the correlations between a majority of liquidity-related spreads increased so substantially during the Great Financial Crisis that they have not reverted to normal correlation levels in the aftermath of the crisis. This finding suggests that, for most spreads, their exposure to a liquidity factor has

[1]Data for a variety of mortgage rates are also available. We use yield spreads from two portfolios for which the construction of long timeseries is possible: a 5-year index of private-label Aaa-rated fixed-rate CMBS yields computed by Bloomberg/Morgan Stanley and an index of 30-year fixed-rate residential prime mortgage rates computed by Freddie Mac. Portfolio index series also exist for lower-rated private-label MBS and CMBS, but these time series are too short for use with the econometric methods applied in this paper.

[2]Such average, subsample unconditional correlations are relevant to long-horizon investors and help identify low-frequency movements in correlations (see, e.g., Engle and Rangel, 2009), net of any low-frequency movements in volatilities.

been substantially altered by the Great Financial Crisis. Second, almost two-thirds of the default risk spread correlations have remained altered even after the Great Financial Crisis, consistent with permanently altered exposures of default-risk-related spreads to a common default risk factor. Third, about half of the correlations between spreads affected by policy interventions have returned to levels that exceed the pre-crisis norm. Pairs of spreads that typically capture default risk (e.g., the Baa–Aaa corporate or the corporate junk spreads) were all simultaneously affected by policy interventions. These spreads may have inherited patterns of behavior in the post-crisis period that reflect the possibility of future interventions. However, the higher correlation levels in the aftermath of the Great Financial Crisis can also be considered as indication that the vast array of policy measures deployed to counter the effects of the crisis may have affected the set of investment opportunities in structural and possibly undesirable ways.[3]

Our findings concerning the failure of many pairwise spread correlations to revert to their normal pre-Great Financial Crisis levels cast doubts on some of the recent literature that has concluded – perhaps too quickly and dismissively – that the crisis was over by mid-2009. Even though means and volatilities of many spreads have indeed returned to their pre-crisis norm, permanently altered (higher) correlations between spreads may also have produced severe long-run effects. In this sense, and possibly in the light of the sovereign debt crisis that has affected the international fixed income markets since 2010, the Great Financial Crisis may have been over much later than commonly believed and possibly beyond the end of our sample.

Using a different methodology and a smaller but more diverse set of underlying assets, a related paper by Dungey et al. (2012) also highlights the possible existence of the structural shifts we discuss in our analysis. Their paper uses a parametric smooth transition structural GARCH model to endogenously detect simultaneous structural shifts in the relationships (dynamic correlations) among U.S. stocks, real estate, and Treasury securities during different stages of the Great Financial Crisis that are consistent with ours (see Section 4.1). A stark outcome of their empirical efforts is that financial conditions in 2009-10 were not back to where they were earlier in the decade and, in particular, that the contemporaneous linkages between bond and stock markets did not return to pre-crisis conditions. Similar to our conclusions, their findings suggest that the Great Financial Crisis left persistent effects at least through 2010. As our main focus is on a larger but more homogeneous set of yields spreads at the epicenter of the Great Financial Crisis, we see our results and theirs as complements. Both Dungey et al. (2012) and we address the problem raised by Dungey and Zhumabekova (2001) that testing for changes in correlations in small samples may seriously affect the power of the test. However, while Dungey et al. (2012) work within a tight parametric framework that allows them to isolate the effects of the correlation variations and rule out potential biases derived from contemporaneous instability in the volatilities, we adopt a

[3]Higher correlations may indicate a diminished diversification potential, as in classical finance theory.

nonparametric framework. In particular, we implement a nonparametric bootstrap methodology to test for breaks in signed pairwise correlations with the objective of characterizing the evolution of correlations without imposing any specific – and potentially misspecified – parametric structure. With a different methodology, we also correct for the small-sample biases discussed in Dungey and Zhumabekova (2001).

Finally, our paper is related to a strand of the literature that proposes increasingly sophisticated models for the dynamics in yield spreads, such as Davies (2008), who analyzes the determinants of U.S. credit spreads over an extensive 85-year period that covers several business cycles. His analysis demonstrates that econometric models are capable of explaining up to one-fifth of the movement in the spreads considered. Interestingly, Davies also reports that maximum explanatory power is achieved using nonlinear econometric frameworks of the regime-switching type. One can interpret our modeling, in which structural change in second moments is allowed, as an additional case for such a regime-type behavior.

The rest of the paper is organized as follows. In Section 2 we sketch the methodological aspects of our empirical investigation. Section 3 is devoted to the description of the dataset and the summary statistics of the 11 spreads over 3 subsequent subsamples of the 2002-11 period. We present our empirical results in Section 4, including details on the dating of the Great Financial Crisis. We conclude in Section 5.

2. Research Methodology

In the next two sections we sketch the methodological aspects of our paper. The extent of the cross-section correlation in a panel of 11 U.S. yield spreads, measured as described in Section 3 and in Guidolin and Tam (2010), is examined using Ng (2006)'s uniform spacings methodology, developed in Section 2.1. Ng (2006)'s approach is multivariate in nature and, regardless of sign, is used to assess the intensity of the cross-section correlation and its variations among the 11 yield spreads over pre-crisis, crisis, and post-crisis periods.

Signed correlation changes between individual pairs of spreads are analyzed by means of a nonparametric bootstrap approach, outlined in Section 2.2. The bootstrap methodology considers two spread series at a time and is intended to analyze correlation changes for each pair of spreads taken separately between pre-crisis and crisis periods and then between crisis and post-crisis periods.

The two statistical techniques are complementary. While the first can help appraise the nature of comovement, its magnitude regardless of sign, and its variations from a multivariate point of view, the second technique is more useful if the goal is to investigate comovement changes and their sign from a more limited and traditional bivariate perspective. Further details are provided in Appendix A and the cited references.

2.1. Testing Cross-Section Correlation in a Panel of Data

We use the theoretical framework developed in Ng (2006) to test for and determine the extent of cross-section correlation in a data panel when the number of series and the specific series that are correlated are unknown ex ante. The test is based on the probability integral transformation of the ordered absolute correlations of all pairs of time series. Standard tests for cross-section correlation in panels of data (e.g., Breusch and Pagan, 1980) are based on the null hypothesis that all pairs of time series exhibit no correlation against the alternative hypothesis that the correlation is different from zero for at least one of the time-series pairs.[4] However, such traditional approaches, which often rely on normality assumptions, provide no indication of the extent of correlation in the panel when the null hypothesis of no cross-section correlation is rejected. From a practical perspective, rejecting the null hypothesis reveals little information about the strength and prevalence of the cross-section correlation. Moreover, when heterogeneity exists in panel correlations, it is difficult to precisely characterize the magnitude of the correlations with a single statistic. On the contrary, Ng's uniform spacings methodology allows the determination of whether at least some (not necessarily all) series in the sample are correlated (regardless of the sign of that correlation). Furthermore, thanks to this approach, the time series responsible for the rejection of the null hypothesis of no cross-section correlation can be precisely identified.

Let M be the number of fixed income spreads in the sample and T the number of time-series observations (in our case, weekly observations; see Section 3). Such spreads need not satisfy any specific distributional assumptions, provided the data sample is sufficiently large. The number of unique elements above (or below) the diagonal of the sample correlation matrix is $N \equiv M(M-1)/2$. Define $\overline{\rho} \equiv (|\widehat{\rho}_1|, |\widehat{\rho}_2|, ..., |\widehat{\rho}_N|)'$ as the vector of sample absolute correlation coefficients that collects the absolute values of the estimates of the population correlations in $\rho \equiv (\rho_1,\ \rho_2,\ ...,\ \rho_N)'$. Let such N sample absolute correlation coefficients be ordered from the smallest to the largest $\left(\overline{\rho}_{[1:N]}, \overline{\rho}_{[2:N]}, ..., \overline{\rho}_{[N:N]}\right)'$. Finally, define $\overline{\phi}_s \equiv \Phi\left(\sqrt{T}\overline{\rho}_{[s:N]}\right)$, where $\Phi(\cdot)$ is the cumulative distribution function of a standard normal distribution and $s = 1, 2, ..., N$. Given that $\overline{\rho}_{[s:N]} \in [0,1]\ \forall s = 1, 2, ..., N$, then $\overline{\phi}_s \in [0.5, 1]\ \forall s = 1, 2, ..., N$. Ng (2006) proves that the null hypothesis of $\rho_s = 0$ is equivalent to the null of $\overline{\phi}_s \sim U[0.5, 1]$. The q-order uniform spacings is defined as $\left\{\left(\overline{\phi}_s - \overline{\phi}_{s-q}\right)\right\}_{j=q+1}^{N}$.[5]

We partition the N sample absolute correlations into two groups: S for small (containing the smallest absolute correlations) and L for large (containing the largest absolute correlations). The fraction of correlations in the sample contained in S is $\theta \in [0,1]$. The methodology estimates θ through maximum likelihood. The goal is to locate a mean shift in the sequence of spacings

[4] Other applications of this methodology are Contessi and De Pace (2009), Herrera et al. (2008), and Byrne et al. (2011).

[5] Ng (2006) explains why, if the underlying correlations are all zero, the uniform spacings $\left(\overline{\phi}_s - \overline{\phi}_{s-q}\right)$ constitute a stochastic process that satisfies statistical properties useful to build optimal tests.

$\left\{\left(\overline{\phi}_s - \overline{\phi}_{s-q}\right)\right\}_{s=q+1}^{N}$ or a slope change in the sequence of $\overline{\phi}_s$'s. The number of correlations in S is $\hat{K} \equiv \hat{\theta}N$, whereas the number of correlations in L is $N - \hat{K} = \left(1 - \hat{\theta}\right) N$. The strategy is to test whether the $\hat{K}$ absolute correlations in S are jointly zero. If the small correlations are statistically different from zero, then the absolute correlations in L must also be different from zero by construction.

A standardized spacings variance ratio (SVR) test statistic is computed to test the hypothesis of zero absolute correlation within each group. The test exploits the fact that the q-order uniform spacings is an integrated process. The test statistic, $SVR\,(n)$, asymptotically (as $n \longrightarrow \infty$) follows a standard normal distribution under the null of no correlation in a subsample of absolute correlations of size $n = N$, $\hat{K}$, or $N - \hat{K}$, depending on which partition of the N sample absolute correlations is considered.[6] The SVR test statistic, which depends on the choice of the lag-length parameter q, is based on a transformation of the yield spread correlation spacings, which are exchangeable by construction – that is, the structure of dependence is the same for $(\overline{\phi}_s - \overline{\phi}_{s-q})$ for any s. This fact implies that the test can be run on any subset of the ordered correlations. If the data are uncorrelated, it can be shown that the $\overline{\phi}_j$'s all lie along a straight line with slope $1/\left[2\left(n+1\right)\right]$ in a Cartesian space. The more prevalent and the stronger the correlation, the further away are the $\overline{\phi}_s$'s are from that straight line. Any partition of the full sample can be used to test the slope of the sequence of $\overline{\phi}_s$'s. In practice, for each group (S or L) we test whether the variance of $\left\{\left(\overline{\phi}_s - \overline{\phi}_{s-q}\right)\right\}_{s=q+1}^{N}$ is a linear function of q, which translates the problem into testing the uniformity and nonstationarity of a specific transformation of sample absolute correlations.[7] If the uniformity hypothesis on the $\overline{\phi}_s$'s is rejected for S, testing whether the same hypothesis holds for L becomes uninformative. If the null of zero correlation is not rejected in S, we can apply the same methodology to partition S (second split) first and obtain two additional subsamples, SS and SL. The test can be run again to determine whether the observations in SS are uncorrelated.[8]

2.2. Testing for Structural Changes in Signed Correlation Coefficients

We use a version of a nonparametric bootstrap technique known as the iterated stationary bootstrap to test for breaks in (signed) pairwise correlations. For each pair of interest rate spreads, we bootstrap the difference between their correlation coefficients over two subsequent subsamples. The breakpoints, $1 < \tau_B < T$, are exogenously given and determined by a variety of techniques

[6] Ng (2006) shows that the method also exhibits reliable small-sample properties.

[7] A simple quantile-quantile (q-q) plot of the $\overline{\phi}_s$s may provide information about the extent of cross-section correlation in the data. If all correlations are nonzero, then the q-q plot will be shifted upward and its intercept will be larger than 0.5. If there is homogeneity in a subset of the correlations, then the q-q plot will be flat over a certain range. If S is characterized by zero correlations while L is not, then in the q-q plot, the $\overline{\phi}_s$'s would be expected to be approximately linear in s until $s = \hat{K}$, then rise steeply for $s > \hat{K}$, and eventually flatten at the boundary of 1.

[8] If there are too few observations in S, then the subsample SS may be too small for the test to be valid. Furthermore, if the SVR test is applied to the SS subsample after the S sample has rejected uniformity, then the sequential nature of the test should be taken into account when making inferences and computing p-values.

that span both narrative accounts of the crisis and formal statistical tests (for details, see Section 4.1). Let ρ_1 be the (true but unknown) correlation coefficient over the first subsample and ρ_2 its value over the second subsample. We test whether the parameter shift, $\Delta\rho = (\rho_2 - \rho_1)$, is statistically significant. Formally, we consider a statistical test with size $(1-\alpha) \in (0,1)$ of the null hypothesis $H_0 : \Delta\rho = (\rho_2 - \rho_1) = 0$ against the alternative, $H_1 : \Delta\rho = (\rho_2 - \rho_1) \neq 0$. In practice, we base our statistical inference on the construction of two-sided, α-level confidence intervals with equal tails derived from the bootstrap distribution of $\widehat{\Delta\rho}$. Iterated bootstrap percentile confidence intervals and iterated bias-corrected percentile confidence intervals are estimated as described in DiCiccio, Martin, and Young (1992) and revisited in De Pace (2013). Significant shifts at the 10 level are indicative of correlation instability.

The bootstrap distribution of $\widehat{\Delta\rho}$ is obtained by resampling data blocks of random length from each pair of time series. Length is sampled from an independent geometric distribution whose expected value equals the expected block size. The original series is *wrapped* around a circle to fill blocks extending past the last observation. Optimal expected length is estimated through an inner (smaller) bootstrap procedure. Bootstrap iterations and, when appropriate, a bias correction are adopted to estimate confidence intervals with improved accuracy. We use $1,000$ replications for the outer bootstrap and 500 for the inner bootstrap.[9]

The advantage of a bootstrap approach in our framework is that it is a more reliable method of testing for changes in correlation coefficients. Basically, statistical inference is often difficult with correlation changes (see Doyle and Faust, 2005, for an explanation of some of the problems that arise when making inferences on correlation coefficients), especially if the data are time dependent and autocorrelated and the samples are small. In such situations, conventional asymptotics cannot provide good approximations for the distributions of estimators and test statistics, thereby rendering the nominal probability of rejecting a true null hypothesis and the true rejection probability very different from each other. When bootstrap techniques are used in alternative forms and under certain conditions, they represent a reliable way of determining the distribution of an estimator, reducing its finite-sample bias, and achieving significant asymptotic refinements in actual versus nominal coverage and size properties of confidence intervals and statistical tests. An important caveat of this methodology is that it applies to correlation changes and does not distinguish whether such variations are due to shifts in common exposures or to shifts in volatility (see Appendix A for a description of the motivation underlying this approach).

[9]A serious trade-off between the number of resamples and computation time must be taken into account. This trade-off advised us to set the total number of bootstraps to a manageable number.

3. Data and Preliminary Evidence

We focus on a set of 11 alternative notions of fixed income yield spreads. These spreads are distinct in terms of the securities/markets to which they refer, the maturity of the underlying securities, and whether they have been affected by specific policy measures that the Fed and policymakers in general have used in reaction to the prolonged financial crisis over the 2007-09 period (Table 1). The sources for all the data series are Haver Analytics and Bloomberg. As in many earlier papers (see, e.g., Christensen et al., 2010; and Longstaff et al., 2005), our data have a weekly frequency. They span the sample period between September 27, 2002, and December 30, 2011, for a total of 484 weekly observations for each spread definition. Listed by increasing maturity, the series concern the following spreads: S1) 3-month LIBOR–overnight indexed swap (OIS); S2) 3-month financial commercial paper (CP)–Treasury; S3) 3-month ABCP–Treasury; S4) 1-year Aaa adjustable-rate mortgage (ARM)–Treasury; S5) 5-year swap–Treasury; S6) 5-year REFCorp strip–Treasury; S7) 5-year commercial private-label CMBS – (the closest, off-the-run) 5-year Treasury; S8) 10-year off-the-run–on-the-run Treasury; S9) 20-year Moody's Baa-rated–Moody's Aaa-rated corporate default spread; S10) 20-year Moody's Bbb-rated–Moody's Aa-rated corporate junk spread; and S11) 30-year conventional fixed-rate mortgage–Treasury. Table 1 lists the exact definitions of the spreads. Relative to the sparse existing literature, we use a much larger number of spreads, some subsets of which are commonly used in other studies as well as in policy analysis, particularly in the context of the financial crisis. For example, Longstaff (2010) use Moody's Aaa and Baa corporate yield indexes vs. 10-year Treasury yield spreads; Manconi et al. (2012) analyze Aaa, Baa, and high-yield corporate bonds, as well as the LIBOR–OIS spread; and Stroebel and Taylor (2012) use various measures of mortgage yields spreads. Hu et al. (2013) use several spreads jointly, including on-the-run premiums for 5-year and 10-year bonds, 3-month LIBOR–3-month T-bill spreads, the Baa–Aaa bond index spread, and the REFCorp strip–Treasury spread. Table 1 also offers additional details regarding whether and how the spreads were directly affected by anti-crisis policy measures, such as the Troubled Asset Relief Program (TARP) or the several waves of quantitative easing (QE) between 2008 and 2011. Table 1 also contains a list of non-exhaustive references to studies in the literature that have used one or more of these spreads.

3.1. Classification of the Spreads

Table 1 provides an overview of the economic nature of the 11 spreads analyzed in this paper. As discussed in the introduction, their direct link with the crisis or the emergency economic policies conducted during the turmoil and their origin from a market that is the core of the crisis itself motivates the inclusion of these spreads in our empirical analysis. We refer to the aforementioned literature and the articles listed in Table 1 to classify the spreads. Six spreads are classified as being directly affected by the policy programs implemented by the Fed and Treasury during the financial crisis, eight spreads are classified as being at high risk of default, six spreads are classified as directly affected by specific policy programs, and four spreads are classified as being short-term.

During the crisis, the LIBOR-OIS spread was a barometer of distress in money markets. The 3-month LIBOR–OIS spread was potentially lowered by the range of swap arrangements among central banks.[10] In May 2008, the Wall Street Journal published an article asserting that several global banks were reporting LIBOR quotes significantly lower than those implied by prevailing credit default swap (CDS) spreads. Some concerns have been raised that after the so-called LIBOR scandal erupted in 2008, the use of the LIBOR rate for academic research may require caution. While we acknowledge that the question remains open, existing research suggests that LIBOR rates remain a valid measure. Abrantes-Metz et al. (2012) compare LIBOR with other short-term borrowing rates between January 2007 and May 2008. They find some anomalous individual quotes, but their evidence is inconsistent with a material manipulation of the U.S. dollar 1-month LIBOR rate. Kuo et al. (2012) report that LIBOR survey responses broadly track alternative measures of borrowing rates. Despite this encouraging evidence, we limit the use of LIBOR rates to only one of the spreads that we consider.

Both the 3-month asset-backed and financial commercial paper spreads were directly targeted by the Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility (AMLF) and Commercial Paper Funding Facility (CPFF) programs. See, for example, Wu and Zhang (2008) for a justification of our focus on financial CP. The 5-year REFCorp strip–Treasury spread was likely indirectly affected by both the Term Asset-Backed Securities Lending Facility (TALF) and the QE programs – in the former case because of direct interventions on the demand of close substitute and highly liquid medium-term bonds, and in the latter case because of the impact on intermediate-maturity Treasury yields.[11]

The 10-year off-the-run–on-the-run Treasury spread was likely affected by the Fed's QE programs because these consisted of open-market purchases of a number of off-the-run issues.[12] Because a few waves of QE directly concerned mortgages securitized by Fannie Mae and Freddie Mac, one of the goals of such interventions was to directly reduce the 30-year Freddie Mac conventional

[10]The 3-month LIBOR is the interest rate at which banks borrow unsecured funds from other banks in the London wholesale money market for a period of 3 months. The OIS rate is the fixed interest rate a bank receives in 3-month swaps between the fixed OIS rate and a (compound) interest payment on the notional amount to be determined with reference to the effective federal funds rate.

[11]The Resolution Funding Corporation (REFCorp) was established in 1989 as the funding arm of the Resolution Trust Corporation to finance the recapitalization of the savings and loan industry. REFCorp issued $30 billion in debt securities between 1989 and 1991. Interest payments on REFCorp bonds are guaranteed by the U.S. government, and the principal is protected by the purchase of zero-coupon bonds with a face value equal to those of REFCorp bonds. While their risk-free credit status is the same as that of Treasury securities, they are much less liquid.

[12]The 10-year off-the-run–on-the-run Treasury spread is the difference between the yield of a Treasury security with a residual maturity of 10 years but not recently issued and the yield of a highly liquid and frequently traded Treasury security (the most recently issued security with a 10-year maturity).

mortgage rate spread.

As far as the financial nature of the spreads is concerned, Table 1 reports a classification for an additional six spreads as representative of liquidity risk premia – that is, the average excess return that investors require to hold less-liquid fixed income securities, such as corporate bonds. The first of these spreads is the 3-month LIBOR–OIS spread, consistent with the fact that this spread has been recently used as an indicator of the liquidity premium (see, e.g., Christensen et al., 2010).[13] The second and third spreads are the 3-month asset-backed (AB) and financial CP spreads; during the crisis, these were hit by a structural shortage of transaction volume. Such a shortage likely made these spreads as reflective of liquidity as of credit risk premia (see Adrian et al., 2010). The 5-year REFCorp strip–Treasury spread is included in this classification because, given that REFCorp bonds are guaranteed by the U.S. government, any differential versus maturity-matched Treasury securities should approximately reflect only the differential depth and resilience of the underlying markets. The 5-year CMBS–Treasury spread also reflects liquidity risk premia because the underlying spot market completely froze between the summer of 2007 and early 2009 (see, e.g., Campbell et al., 2011); the thawing of these spreads was driven by the effects of the TALF program. The 10-year off-the-run–on-the-run Treasury spread is commonly interpreted as a measure of the market liquidity risk premium because two Treasury securities with identical maturities should imply identical credit risk and differ only for the higher "convenience yield" of a highly traded security over another security that is traded infrequently.

Table 1 also classifies 8 of the 11 spreads investigated in this paper as reflecting credit-risk-related factors, on the one hand, because our spreads are often computed with reference to Treasury yields. The credit quality of the U.S. government is shared only by REFCorp bonds. However, Table 1 also lists 2 pure default risk spreads, the 20-year corporate Baa–Aaa and the 20-year Bbb–Aa junk spreads. On the other hand, given that a number of spreads reflect both liquidity and credit risk components, they are listed under both the "liquidity" and the "default" risk columns of the table.[14] Only 3 spreads, which in Table 1 are not reported to reflect a default risk premium, are indeed "pure" proxies of liquidity risk: the 3-month LIBOR–OIS, the 5-year REFCorp strip–Treasury, and the 10-year off-the-run–on-the-run Treasury spreads. Table 1 also presents a simple and objective classification of the spreads by distinguishing between short- and medium-/long-term spreads. All fixed income securities with a maturity of less than 18 months are labeled as short-term securities.

[13]The nature of the LIBOR–OIS spread is not completely clear. At face value, the spread measures a credit risk premium; while the LIBOR, referencing a cash instrument, reflects both credit and liquidity risk, the OIS is a swap rate and as such has little exposure to default risk because swap contracts do not involve any initial cash flows. However, the typical default risk implicit in LIBOR rates is modest.

[14]In the case of private-label Aaa CMBS, we compute a spread with reference to the closest (off-the-run) 5-year Treasury. The choice of an off-the-run Treasury allows us to attribute the CMBS spread to credit risk in the form of a higher probability of future defaults on the mortgages included in the securitized pools vs. Treasury securities.

3.2. Summary Statistics

Table 2 provides a comparison of the main summary statistics (mean, median, standard deviation, interquartile range, skewness, and excess kurtosis) of the 11 spreads over 3 subsequent subsamples of the 2002-11 period (see, e.g., Guidolin and Tam, 2010, and references therein, or Section 4.1 for the rationale behind the determination of the three subsamples): before the crisis (September 2002–July 2007, a sample of 253 weeks), during the Great Financial Crisis (August 2007–June 2009, a sample of 100 weeks), and after the crisis (July 2009–December 2011, a sample of 131 weeks). The pre-crisis period is easy to characterize: Spreads were on average low, often lower than average spreads over the full sample (unreported). The medians are also small and not very different from the means, which is reflected by the modest and often not statistically significant skewness coefficients. The volatilities of the spreads are tiny, always between 5 and 36 basis points (bp) per week (the volatility of the 1-year ARM–Treasury spread appears to be an outlier) and with moderate differences compared with the interquartile ranges.

During the crisis period, all mean spreads increase, reaching levels between two and nine times the pre-crisis means. The only exception is the 30-year fixed-rate mortgage spread, whose mean increases by a timid 44%. Medians are often quite different from the means, and skewness coefficients are often positive and statistically significant. Both the standard deviations and the interquartile ranges increase greatly during the crisis. Standard deviations range from 19 bp per week for the off–on-the run Treasury spread to 446 bp for the 5-year CMBS–Treasury spread. The only exception is again the 30-year fixed-rate mortgage rate, whose volatility increases during the crisis by only 11%.

All means and volatilities decline between the crisis and the post-crisis period. For as many as 3 of the 11 spreads, the post-crisis period is characterized by means and medians substantially lower than the respective pre-crisis means and medians. For as many as six spreads, the post-crisis volatilities are smaller than the pre-crisis ones. There are only two exceptions. The post-crisis mean of the 5-year REFCorp strip–Treasury spread remains abnormally high at 56 bp (the pre-crisis mean is 9 bp), while its volatility remains high at 17 bp per week (the pre-crisis volatility is 11 bp). The same occurs with the 5-year CMBS–Treasury spread, with means and volatilities of 318 bp and 88 bp per week compared with pre-crisis levels of 76 bp and 15 bp, respectively.

Figure 1 offers a visual summary. For the sake of clarity the figure plots standardized spreads. The standardization is applied using unconditional means and standard deviations over the full sample. A large positive (negative) standardized spread marks a large deviation in excess of (below) the mean by historical standards. Figure 1 consists of four different panels obtained by organizing the spreads using the same classification criteria as in Table 1. The Great Financial Crisis period is represented by a shaded band. The first plot concerns the six liquidity-related spreads. All spreads decline to low levels between late 2005 and mid-2007. All series quickly pick up between December 2008 and March 2009. However, a few spreads (such as the 3-month ABCP and financial CP spreads) seem to anticipate such an end-of-2008 swing by exceeding their respective historical norms by 2 to 3 standard deviations between the spring and the summer of 2008 (i.e., the so-called subprime real estate stage of the Great Financial Crisis; see Aït-Sahalia et al., 2009). All spreads start to quickly decline in the late spring of 2009 and reach levels in line with their respective historical experiences by mid-2011. The REFCorp strip–Treasury spread remains slightly elevated, probably indicating persistent and abnormally high liquidity premia related to the European sovereign crisis that intensified in 2010.

The upper-right panel of Figure 1 shows the dynamics of the 7 default risk-related spreads. The general patterns are similar to those just described for the liquidity-related spreads, even though mortgage rate spreads are already high as early as late 2006. All spreads start to decline in the spring of 2009 after peaking in late 2008. They all bottom out at either their typical, historical levels (e.g., for the 3-month ABCP–Treasury and the corporate default spreads), or they even decline below such levels (e.g., for the 30-year fixed-rate mortgage spread and the 5-year swap–Treasury spread) during most of 2010 and in early 2011. This behavior is probably also a result of policy interventions. Interestingly, the 2 corporate bond spreads seem to peak slightly later than the other spreads, around mid-2009. However, by the end of 2011, all spreads returned to levels consistent with historical norms. In general, the first two plots of Figure 1 describe spread dynamics consistent with the conventional wisdom that the Great Financial Crisis was already over between the spring and fall of 2009 (see, e.g., Adrian et al., 2010; Aït-Sahalia et al., 2009; Brave and Genay, 2011; Campbell et al., 2011; Guidolin and Tam, 2010; Hancock and Passmore, 2011).

The lower-left plot of Figure 1 is devoted to the spreads that, according to the classification in Table 1, were affected by the policy interventions implemented during the crisis. The general patterns are similar to those outlined above. The 10-year off-the-run–on-the-run spread appears to be very volatile. Such volatility, however, stems from the mechanical fact that this spread is characterized by a low standard deviation. As such, deviations from the historical mean tend to be magnified. With the only exception of the 5-year REFCorp strip–Treasury liquidity spread, most policy-affected spreads tend to decline below their standardized norms starting in mid-2010 and remain at low levels until the end of the sample.[15] The lower-right plot in Figure 1 concerns the four short-term spreads; their overall patterns are similar to those just discussed.

We used standard augmented Dickey-Fuller unit root tests to show that it is sensible to analyze the interest rate spreads under the assumption of covariance stationarity (results unreported).[16]

[15] A similar pattern for the 10-year off-the-run – on-the-run Treasury spread is hidden by the variability of this time series. For instance, between 2002 and 2007 this spread averaged 14 bp, but then it declined to a mean of 13 bp after mid-2009.

[16] In economic terms, there is a strong case in favor of stationarity. A spread containing a unit root will eventually

The number of lags to be included in the test regressions is selected by minimizing the Bayesian information criterion (the maximum number of lags is 12). Alternative, nonparametric Phillips-Perron unit root tests, which control for serial correlation, was also used. The rejection of the null hypothesis suggests covariance stationarity for the series under investigation. Our results show that yield spread series are generally covariance stationary. Using the Phillips-Perron test, in 8 of 11 cases the p-value is lower than 5%; in one case, the p-value is between 5% and 10%. The evidence favoring covariance stationarity of the spreads is largely confirmed by the augmented Dickey-Fuller tests.[17]

4. Empirical Results

4.1. Dating the Great Financial Crisis

The first step to properly characterize the properties of cross-section spread correlations and their behavior over the cycle is to date the Great Financial Crisis. We approach this task in three different ways and obtain similar dates for the beginning and the end of the crisis from all three methods.

The first approach is heuristic. We reviewed the literature on the Great Financial Crisis to detect systematic patterns in the reported dating efforts. Space constraints do not allow a thorough discussion of the details in the literature. However, even a superficial reading reveals that most papers and articles agree on early August 2007 as a potential starting date of the crisis.[18] In a few cases (e.g., Furceri and Mourougane, 2009; Sarkar, 2009), several different stages within the Great Financial Crisis are isolated and discussed. Only a handful of papers venture into establishing an end date for the Great Financial Crisis (see e.g., Aït-Sahalia et al., 2009; Campbell et al., 2011). An end date can generally be found only in papers written or revised since early 2009. Usually these papers generically claim that the effects of the crisis were reabsorbed around mid-2009 (the end of June then represents a natural end date for the crisis). However, most of these papers establish this dating in a casual fashion and are often based on the analysis of only a few selected time series. The breakpoints are not determined by the techniques applied time-series econometricians would typically use to locate a breakpoint in time.

The second approach is formal and based on the assumption that, over the considered sample,

become negative and spend an infinite time providing negative compensation to credit and liquidity risks. This occurrence makes little sense. See the discussion in Batten et al. (2005).

[17] The only series for which it is difficult to reject the null of a unit root is the 1-year ARM–Treasury spread. As already argued, though, a unit root in a yield spread series is inconsistent with the interpretation of that spread as a risk premium. In this work we assume stationarity also for this particular real estate spread. All results concerning pairwise correlations involving this spread should be interpreted with some caution.

[18] A few papers implement formal statistical approaches to the dating of the Great Financial Crisis. Aït-Sahalia et al. (2009), Frank and Hesse (2009), and Furceri and Mourougane (2009) date the beginning of the subprime crisis back to June-July 2007.

the Great Financial Crisis period is accompanied by structural shifts in the parameters describing the processes that govern the dynamics of the individual interest rate spreads. The breakpoint test methods are illustrated in Guidolin and Tam (2010). They apply Chow and Quandt-Andrews breakpoint tests to univariate and bivariate partial correction models of individual weekly yield spread series similar to those investigated in this paper to "date" the Great Financial Crisis. Even though most commentaries during the crisis drew attention to the level of yield spreads as indicators of market disruption, their results show that the crisis had the power to affect the persistence structure – more precisely, the typical average duration of shocks – of the process describing the evolution of these spreads. They analyze 7 of the 11 spreads considered herein and find that the Great Financial Crisis started in early August 2007 and ended in late June 2009. In this paper, we repeat the analysis in Guidolin and Tam (2010) for our set of 11 yield spreads. Chow tests detect a break in early August 2007 (August 3, 2007) for 8 of the 11 series. Additionally, for all the spreads under consideration, conditioning on a first break occurring in the first week of August 2007, there is evidence of a second break in June 2009 (June 26, 2009), which we interpret as statistical evidence of the end of the Great Financial Crisis. When the two break dates are jointly specified, both the F and log-likelihood ratio versions of the Chow test yield very small p-values and indicate rejection of the null hypothesis of no breaks at the specified breakpoints. Moreover, Quandt-Andrews tests (in which the break dates are unknown and directly estimated) reveal evidence of one break in the case of only two series, the 3-month ABCP–T-bill and the 5-year swap–Treasury, in late 2008. There is evidence of two breaks in three series and three breaks in the remaining six series.[19] When at least two breaks emerge, the first break occurs between April 2007 (for the 5-year CMBS–Treasury spread) and early 2009 (for the 3-month financial ABCP–T-bill spread). All these breaks are detected at a very high level of statistical significance and correspond to a "crisis-onset" shift. A second break affects eight spreads with an estimated date that ranges between March 2009 (for the 3-month LIBOR–OIS spread) and December 2009 (for the off-the-run–on-the-run Treasury spread), which likely marks the exit from the crisis.

The third approach is also based on formal statistical tests but is multivariate in nature and extends beyond the conditional mean of the spread series. We estimate two unrestricted vector autoregressions (VAR) of orders 1 and 2 using the levels of the 11 interest rates spreads over the full sample. Both VARs satisfy the conventional stability conditions that ensure stationarity and are also consistent with our earlier stationarity results (unreported). Because of the univariate results outlined above, we follow the quasi-maximum likelihood approach described in Qu and Perron (2007) to estimate two breaks at unknown dates in the coefficients of the VARs and in the variance-covariance matrices of the errors of the two multivariate models. The errors are assumed

[19]The second (third) break is obtained from a Quandt-Andrews test that conditions on the first (second) break. When three breakpoints are estimated, there is evidence of a more recent break in 2011, which one may conjecture as being related to the European sovereign and bank debt woes.

to be normal.[20] The covariance matrices of the errors in the two models and the distributions of the regressors are allowed to change from one regime to the next. The error terms are allowed to be autocorrelated, but no prewhitening is applied when we construct the confidence intervals for the breakpoints. Under a VAR(1) model specification, the two estimated breaks are August 3, 2007, and July 17, 2009. The corresponding confidence intervals are very narrow: [7/27/2007, 8/3/2007] and [7/24/2009, 7/31/2009], respectively.[21] These two breaks are close to the breaks resulting from the heuristic approach and the formal univariate Chow tests.[22]

Based on the previous discussion, the Great Financial Crisis starts in the summer of 2007 (during the week ending on August 3, 2007) and ends in the early summer of 2009 (during the week ending on June 26, 2009). We split the sample into three parts: (i) the pre-crisis sample $[1, T_1]$, where T_1 is the week ending on July 27, 2007; (ii) the crisis period $[T_1 + 1, T_2]$, where T_2 is the week ending on June 26, 2009; and (iii) a post-crisis period, $[T_2 + 1, T]$, where T corresponds to the last week of the overall sample, the week ending on December 30, 2011.

4.2. Cross-Section Correlation Tests

Table 3 reports the signed correlations between spreads over the three subperiods isolated in Section 4.1: September 27, 2002–July 27, 2007 (pre-crisis period), August 3, 2007–June 26, 2009 (Great Financial Crisis), and July 3, 2009–December 30, 2011 (post-crisis period). The average cross-section absolute correlation between the series increases moderately during the Great Financial Crisis, from 0.406 before the crisis to 0.462 during the crisis. The average absolute correlation returns to 0.409 in the aftermath of the crisis. Even though the average absolute correlations are very similar in the pre- and post-crisis periods, the differences across individual signed pairwise correlations between the two periods are substantial and suggest the occurrence of complex dynamics in the U.S. fixed income markets. A more careful analysis of the table reveals that in the second subsample, 53% of the correlations increase in absolute value. In particular, the absolute correlations between the spreads associated with long-term securities increase more frequently (71% of the possible 21 pairs). Conversely, after the Great Financial Crisis, 56% of the absolute correlations decline toward their pre-crisis values. This decline is particularly strong for long-term spreads (67%

[20] The distribution of the test statistics becomes degenerate as the estimated breaks approach the beginning or the end of the equation sample, or if the two breaks are too close to each other. To compensate for this behavior, we impose a value of 15% (73 weeks) for the trimming parameter (i.e., the minimum distance between the two breaks, between the beginning of sample and the first break, and between the second break and the end of sample).

[21] This strategy is similar to that adopted by Doyle and Faust (2005) and De Pace (2013), who determine breaks in the processes of a set of macroeconomic variables and then statistically study the evolution of their moments over the resulting subsamples. The detected breaks may not correspond to the breaks in bivariate correlation coefficients, which may differ across the spreads. Our assumption is that some features of the VARs break at some point in time. Later in this paper we test that others remain constant. In this context, the features in which we are interested–unconditional correlations–can be written as scalar functions of the VAR parameters.

[22] In the second case, under a VAR(2) model specification, the two breaks are August 8, 2007, and February 13, 2009. Their confidence intervals are wider: [7/27/2007, 8/17/2007] and [2/6/2009, 2/20/2009], respectively.

of the cases). Nevertheless, between the second and third subperiods, 61% of the 28 mixed absolute correlations (i.e., the absolute correlations involving spreads associated with short- and long-term bonds) decline. The standard deviation of the pairwise absolute correlations increases considerably during the Great Financial Crisis but does not return to the low value of the first subperiod in the aftermath of the crisis.

Table 3 has some limitations. Despite the wealth of information that it contains, it does not allow determining whether there are significant changes in the overall degree of cross-spread correlation associated with the Great Financial Crisis. Table 4 proposes a battery of Ng tests based on the absolute correlations. In the pre-crisis period, there is strong evidence that the hypothesis of no cross-section correlation may be rejected irrespective of the choice of the lag-order parameter q, with p-values ranging from 0.1% to 2.6%. The lower panel of Table 4 shows that this cross-section correlation is due to a large set of 49 pairs of spreads with large pairwise absolute correlations, which determine the rejection of the null hypothesis of no correlation at least for $q = 2$.

Although the statistical evidence for $q = 2$ is weaker, the null hypothesis of no cross-section absolute correlation is also rejected over the Great Financial Crisis period. This rejection is the result of a group of 48 correlations that are jointly and statistically different from zero for $q = 4$ and $q = 6$. In the aftermath of the financial crisis, spreads are still correlated. In Table 4, the null hypothesis of no cross-section correlation can always be rejected independently of the choice of the parameter q. The null hypothesis of zero cross-section correlation for the group of large correlations is also rejected independently of q.

These results confirm a strong statistical evidence of nonzero absolute correlations for the large majority of the 55 pairs of spreads. In the next section, we test whether the pairwise signed correlations between spreads significantly change between subperiods.

4.3. Evidence of Correlation Instability

The cross-section of spreads is characterized by massive and statistically significant correlations. Each panel of Figure 2 plots 55 pairs of ordered absolute correlations in any two different subsamples in a Cartesian space. The figure considers three possible combinations: the ordered correlations from (i) the pre-crisis to the Great Financial Crisis sample, (ii) from the Great Financial Crisis to the post-crisis sample, and (iii) from the pre-crisis to the post-crisis sample. The first two scatterplots are based on a natural time evolution of events. The last plot allows us to see whether the Great Financial Crisis had persistent effects in the pairwise correlations. In each panel the correlation pairs would approximately lie along the dashed 45-degree line if the magnitude of correlations were stable between subperiods. For example, the closest dot to the origin in the top-left graph represents the lowest absolute correlation observed in the pre-crisis period (the value shown on the horizontal axis) paired with the lowest absolute correlation observed in the crisis period (the value shown on the vertical axis). In this sense, each dot does not match pairs of spreads over the two subperiods.

Figure 2 shows that a majority of the correlations increased when the U.S. financial markets entered the Great Financial Crisis. At least 25 pairs are located well above the 45-degree line in the first plot. This phenomenon mainly concerns the largest values of absolute correlations. The smallest values of absolute correlations decline modestly between the two periods. The second plot shows that the smallest values of absolute correlations are essentially steady between the Great Financial Crisis and the post-crisis periods when the largest values tend instead to decline. The last plot shows modest differences between the pre-crisis and the post-crisis periods. This finding is likely consistent with a cyclical pattern in which the Great Financial Crisis alters ordered pairwise correlations by increasing their absolute value. These correlations decline after the crisis.

The Great Financial Crisis can be seen as a period of structural change during which correlations between yield spreads are systematically altered, possibly (but not necessarily) as a consequence of the soaring exposure of the securities underlying those spreads to common crisis factors, such as disappearing risk appetites, liquidity shortages, and funding problems for intermediaries often engaged in market-making activities in fixed income markets. In addition, a growing literature in macroeconomics is studying the relationship between measures of uncertainty or financial stress and macroeconomic outcomes that may also alter the correlations we study, although these studies tend to rely on lower-frequency data.

Nonetheless, the evidence depicted in Figure 2 is not conclusive. First, it plots only the absolute values of pairwise correlations, discarding their sign. Second, the figure does not show whether the correlation changes are statistically significant. Third, the panels are so compact that cases in which correlations may have increased during the Great Financial Crisis and never reverted to normal levels could be hidden. An interpretation of this movement is that a structural change in the relationship between pairs of spreads may have occurred in the interim. Figure 3, which plots signed pairwise correlations in the three subsamples, shows a partial investigation of this possibility. Each dot matches the same pair of spreads over the two subperiods represented along the axes.

Even when signs are taken into account, most pairs of correlations lie above the 45-degree line between the pre-crisis and the crisis samples (the first panel in Figure 3). The few dots below the no-change line represent modest correlation declines. On the other hand, many of the dots above the dashed line represent substantial increases. In particular, the second quadrant of the Cartesian cross contains 8 pairs of spreads that exhibit negative and rather large correlations (around -0.5) before the crisis and positive correlations during the crisis. As emphasized in the previous context of ordered absolute correlations, many correlations that were already large before the crisis increase even more during the Great Financial Crisis.

The second panel of Figure 3 shows a mild prevalence of declining correlations between the

Great Financial Crisis period and the post-crisis sample. In particular, there is a dense cloud of a dozen spreads in the first quadrant, whose large and positive correlations somewhat decline in the aftermath of the crisis. In the third panel, the analysis of the changes between the pre-crisis and the post-crisis periods shows that signed correlations increase over time for approximately two-thirds of the spreads.

The second row of Figure 3 contains the elements presented in the first row for which the null hypothesis of no correlation shift between two subperiods is rejected. That is, the three panels contain dots corresponding to the pairs of spreads i and j such that $i \neq j$ for which the null hypothesis $\Delta\rho_{i,j} = \left(\rho_{i,j}^{[T_1+1,T_2]} - \rho_{i,j}^{[1,T_1]}\right) = 0$, $\Delta\rho_{i,j} = \left(\rho_{i,j}^{[T_2+1,T]} - \rho_{i,j}^{[T_1+1,T_2]}\right) = 0$, or $\Delta\rho_{i,j} = \left(Corr_{i,j}^{[T_2+1,T]} - Corr_{i,j}^{[1,T_1]}\right) = 0$ is rejected with a p-value of 10% or lower. The far-left panel reinforces the view that the Great Financial Crisis is characterized primarily by strongly increasing correlations (22 of the 55 correlations significantly increase between the first period and the second). Only the correlations among three spread pairs (the 20-year corporate Bbb–Aa junk spread matched to the 5-year interest rate swap–Treasury and 3-month ABCP–T-bill spreads; and the paired 3-month LIBOR–OIS and 1-year ARM–T-bill spreads) decline in a statistically significant manner. Between the pre-crisis and the crisis subsamples, we observe a heterogeneous trend: A dozen pairs, mostly overlapping with the 22 pairs that drift up between late 2007 and mid-2009, in this case drift down toward lower correlation levels. However, the correlations of another eight pairs increase as if they were hit by the crisis later than the rest of the financial market. As shown below, such occurrences often may be related to the effects of policy interventions. The third panel shows (different from the first row) that for almost half (22) of the 55 pairs of spreads, the Great Financial Crisis indeed left fixed income spreads significantly more correlated than before the crisis.

However, the three plots in the second row of Figure 3 remain opaque as to which pairs of spreads are characterized by statistically significant correlation changes. We therefore use the results from tests reported in Table 5 to determine exactly which pairs of spreads underwent the cyclical pattern previously discussed. Panel A concerns changes in signed correlations between the pre-crisis and Great Financial Crisis subsamples. The upper table shows changes in correlations; in the middle table boldface indicates significant correlation changes. When the financial markets entered the Great Financial Crisis, 38 correlations grew, whereas only 17 declined. Moreover, 21 of the upward movements but only 4 of the downward movements were statistically significant. A cluster of pairs involving the 1-year ARM–Treasury, 5-year private-label CMBS–Treasury, and the 3-month LIBOR–OIS spreads is characterized by a strong widespread significant increase in correlations.

Panel B in Table 5 shows the changes in correlations between the Great Financial Crisis and the post-crisis subsamples. Even though only 25 of 55 correlations decline, 13 of these 25 do so in a statistically significant way.[23] For consistency with Figure 3, we have also analyzed how correlations changed between the pre- and post-crisis periods. About half of the correlations significantly changed. The number of significant increases is 22; there are 5 significant declines.

4.4. Which Spreads Were Affected by the Crisis and How?

The analysis presented in the previous sections does not shed light on the factors underlying the correlation instabilities detected. Figures 4 and 5 are devoted to this final task. The three graphs in the first row of Figure 4 plot the correlation combinations involving only the yield spreads with a liquidity premium (see the classification in Section 3.1). More precisely, these coordinates concern only correlations computed for spreads that are liquidity driven. The circled coordinates correspond to statistically significant correlation changes. Almost all the "liquidity correlations" increase from the pre-crisis to the Great Financial Crisis subsample and about half of them do so in a significant fashion. The correlations between liquidity-related spreads do not generally increase after the Great Financial Crisis; two of them significantly decline. These patterns are not found in mixed pairs, which include liquidity and non-liquidity yield spreads (detailed results are available upon request). The overall signed correlation increases are visible in the third plot (where the pre-crisis and the post-crisis periods are considered), which shows a majority of significantly positive changes. Even though a liquidity factor is likely to have contributed to the correlation increases, there is weak evidence that such correlations reverted to their normal pre-crisis levels.

The second row in Figure 4 plots the correlation combinations between pairs of spreads that either represent or are heavily related to default risk. The dynamics are qualitatively similar to those already found, although they are quantitatively weaker because only a minority of the correlation changes are statistically significant. However, several correlations seem to continue to drift upward even after the end of the Great Financial Crisis. As a result, almost two-thirds of the default risk spread correlations do remain altered after the crisis. About a dozen such changes are significantly positive and seemingly permanent. One possible interpretation of the three middle graphs in Figure 4 is a permanently altered exposure of default-risk-related fixed income spreads to a common default risk factor.

In the bottom row of Figure 4 we plot the correlations between pairs of spreads that were likely affected by policy interventions during the crisis. The pattern of correlation – increases between the pre-crisis and the crisis periods, followed by correlation decreases in the post-crisis sample – is confirmed. Of note, in the first panel only the positive correlation changes are sometimes statistically significant; in the second panel only the negative correlations changes are, in a few cases, significant. The third panel, which compares the pre-crisis and the post-crisis periods, also

[23] Of the 30 correlations that increase in the aftermath of the Great Financial Crisis, only 8 do so in a statistically significant fashion.

reveals that while about 20% of the correlations affected by policy interventions eventually decline below their pre-crisis levels, about half of them eventually return to correlation levels exceeding the pre-crisis ones. In fact, the pairs of spreads simultaneously affected by policy interventions may have either inherited patterns of behavior in the post-crisis period that reflect the possibility of future additional interventions to correct market excesses (e.g., emergency liquidity programs such as the Term Auction Facility [TAF] and the TALF) or may have simply been affected by some types of additional measures during the post-crisis period. The latter is indeed plausible because of the two waves of QE covered in our analysis.[24]

Figure 5 presents three sets of additional plots. The figure describes pairwise correlations for short-term spreads only (top row of scatterplots), long-term spreads only (middle row of plots), and mixed cases involving both short- and long-term spreads (bottom row of plots). Similar to (most) yield spreads affected by policy interventions, the typical pattern is characterized by strong and often significant correlation increases between the pre-crisis and the crisis periods and between the pre-crisis and post-crisis periods. The right-side plots for each set clearly show that the financial crisis left a vast majority of yield spreads more correlated than before the crisis despite the mild (sometimes significant) correlation declines experienced by some pairs of spreads between the Great Financial Crisis period and the aftermath of the financial turmoil.

In Appendix B, we describe the details of a heuristic theoretical framework, which helps in interpreting the empirical findings discussed in this section.

5. Conclusion

In this paper, we have systematically investigated the empirical behavior of the correlations of 11 U.S. fixed income yield spreads over a 2002-11 period surrounding the so-called Great Financial Crisis of 2007-09. We have used a combination of cross-section methods to determine the existence of nonzero correlations in groups of spreads and break tests concerning pairwise correlations to provide a novel characterization of the Great Financial Crisis. Our results indicate that during the crisis most pairwise correlations between yield spreads were systematically and significantly altered in the sense of spreads comoving with one another much more strongly than in normal times. These results should be contrasted with the more traditional studies that have examined either the effects of the Great Financial Crisis on spreads only at a univariate level (see, e.g., Guidolin and Tam, 2010) or those focused only on its effects on the (conditional) mean and variance of the spreads. For instance, Nippani and Smith (2010) study the spread between the 10-year interest rate swap and the

[24] One may argue that if the financial crisis has significantly and permanently affected the correlations between spreads, then the policies implemented by the Fed and the Treasury must have had limited effects at best. Yet, it is also possible that, just because these policy measures have been highly effective, then the correlations of (some) pairs of yield spreads directly affected by policy interventions may have not reverted to their pre-crisis levels.

10-year U.S. Treasury security as the measure of the risk associated with Treasury securities during the financial crisis. They highlight that the spread decreases in level and becomes more volatile as the crisis progressed. Our work confirms the heuristic idea that the Great Financial Crisis was also a period of structural and systematic alteration of correlations possibly (but not necessarily) induced by the common and soaring exposures of the securities underlying the spreads to common crisis factors (such as disappearing risk appetites, liquidity shortages, and funding problems for intermediaries).

The adoption of a nonparametric bootstrap approach provides evidence that for almost half of the 55 pairs of spreads investigated, the Great Financial Crisis has left fixed income spreads more highly correlated than before the crisis. This evidence appears particularly strong for three (occasionally overlapping, but clearly defined) subsets of spread pairs. From a financial point of view, significantly altered correlations might affect investment decisions and the composition of portfolios and their characteristics in terms of diversification. We have also discussed which factors might have driven the correlations during and after the Great Financial Crisis. First, we found evidence that increase of the correlations of the majority of the liquidity-related spreads during the Great Financial Crisis was so substantial that they have failed to revert to normal levels after the crisis. The exposure of most spreads to a liquidity factor appears to have been substantially increased by the Great Financial Crisis. Second, almost two-thirds of the default risk spread correlations remained altered even after the Great Financial Crisis. This finding is consistent with permanently altered exposures of default-risk-related spreads to a common default risk factor. Third, about half of the correlations affected by policy interventions eventually reached levels exceeding the pre-crisis standards. This result may be deemed a powerful indication of the possibility that the broad array of policy measures deployed to counter the effects of the crisis in fixed income markets structurally affected the set of investment opportunities. While it would be interesting to use a factor model similar to (or even more general than) the one discussed in Appendix B – not only to frame our main results but also to directly specify and estimate such a factor model for our fixed income spreads – we leave this extension to future work.

Finally, our findings regarding the failure of many pairwise spread correlations to revert to their pre-Great Financial Crisis levels cast doubts on the results of some of the recent literature that may have too quickly and dismissively concluded that the crisis was over as early as mid-2009. Even though means and variances of many spreads have returned to their pre-crisis norms, permanently altered (higher) correlations between spreads may produce undesirable long-run effects. An important implication of our results is that the Great Financial Crisis may have come to an end much later than commonly believed and possibly beyond the last observation in our sample.

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Appendix A

In Appendix A, we describe the procedure used to construct bootstrap distribution for $\widehat{\Delta\rho}$ and to derive accurate confidence intervals for $\Delta\rho$.

Constructing Stationary Bootstrap Distributions

Let ρ be the parameter under investigation (a correlation coefficient between two time series), ρ_1 its true value over the first subsample, and ρ_2 its true value over the second subsample. We are interested in testing whether the parameter shift, $\Delta\rho = (\rho_2 - \rho_1)$, is statistically significant. Formally, we consider a statistical test with size $(1-\alpha) \in (0,1)$ of the null hypothesis that $H_0 : \Delta\rho = (\rho_2 - \rho_1) = 0$ against the alternative that $H_1 : \Delta\rho = (\rho_2 - \rho_1) \neq 0$. In the simple case of two interest rate spreads, A and B, let $X_{A,t} \equiv \{X_{A,s}\}_{s=1}^{T}$ and $X_{B,t} \equiv \{X_{B,s}\}_{s=1}^{T}$ denote two observed time series, and let τ_B be an exogenous breakpoint that is assumed to have occurred after the first and before the Tth time series observations. Each series is thus split into two subsamples, $X_{A,t}^{1}=\{X_{A,s}\}_{s=1}^{\tau_B}$, $X_{B,t}^{1}=\{X_{B,s}\}_{s=1}^{\tau_B}$, $X_{A,t}^{2}=\{X_{A,s}\}_{s=\tau_B+1}^{T}$, and $X_{B,t}^{2}=\{X_{B,s}\}_{s=\tau_B+1}^{T}$. Let $\rho\left(X_{A,t}^{1},X_{B,t}^{1}\right)=\rho_1$ and $\rho\left(X_{A,t}^{2},X_{B,t}^{2}\right)=\rho_2$. In the first subsample, let $w_{A,i,l}$ and $w_{B,i,l}$, respectively, denote the blocks $\left\{X_{A,s}^{1}\right\}_{s=i}^{i+l-1}$ and $\left\{X_{B,s}^{1}\right\}_{s=i}^{i+l-1}$ of length l starting at $X_{A,i}^{1}$ and $X_{B,i}^{1}$, with $X_{A,i}^{1}=X_{A,1+\{(i-1)\mathrm{mod}(\tau_B)\}}^{1}$, $X_{B,i}^{1}=X_{B,1+\{(i-1)\mathrm{mod}(\tau_B)\}}^{1}$, $X_{A,0}^{1}=X_{A,\tau_B}^{1}$, and $X_{B,0}^{1}=X_{B,\tau_B}^{1}$. Finally, let I_1, $I_2,...$ be a sequence of random numbers independently drawn from a uniform distribution defined on the integers $1,...,\ \tau_B$, and let L_1, $L_2,...$ be a sequence of random numbers independently drawn from a geometric distribution, $\Pr(L=l)=\lambda(1-\lambda)^{l-1}$ with $l=1,2,...$[25] Given an estimate of the factor $1/\lambda$, the bootstrap algorithm that generates the pair of stationary bootstrap time series replicas for A and B over the first subsample, $X_{A,t}^{1*}$ and $X_{B,t}^{1*}$, runs as follows:

1. Set $X_{A,t}^{1*}=w_{A,I_1,L_1}$, $X_{B,t}^{1*}=w_{B,I_1,L_1}$, and $j=1$;
2. while *length* $\left(X_{A,t}^{1*}\right)<\tau_B$, increment j by 1 and redefine $X_{A,t}^{1*}$ and $X_{B,t}^{1*}$ as $X_{A,t}^{1*}\equiv X_{A,t}^{1*}\cup w_{A,I_j,L_j}$ and $X_{B,t}^{1*}\equiv X_{B,t}^{1*}\cup w_{B,I_j,L_j}$, where *length* (Z_t) is the number of observations that compose the time series Z_t;
3. if *length* $\left(X_{A,t}^{1*}\right)>\tau_B$, discard the two series of pseudo-data just generated and restart resampling from (i) after drawing new sequences of random numbers, I_js and L_js.

We apply this scheme to both the first and the second subsample N_O^B times. In correspondence with each complete resample from the original data, we estimate and collect $\widehat{\Delta\rho}^*=[\widehat{\rho}\left(X_{A,t}^{2*},X_{B,t}^{2*}\right)-\widehat{\rho}\left(X_{A,t}^{1*},X_{B,t}^{1*}\right)]$ to estimate the bootstrap distribution of $\widehat{\Delta\rho}$.

Estimating Accurate Confidence Intervals

Let $X_{A,t}$ and $X_{B,t}$ be two time series and $I_0\left(\alpha;X_{A,t},X_{B,t};X_{A,t}^{*},X_{B,t}^{*}\right)$ the uncorrected bootstrap percentile confidence interval with nominal coverage probability α for a change in the parameter ρ, $\Delta\rho$. $X_{A,t}^{*}$ and $X_{B,t}^{*}$ are two generic resamples with replacement from $X_{A,t}$ and $X_{B,t}$. I_0 is constructed from sample and resample information. In empirical applications, the coverage probability of I_0 – namely, $\Pr(\alpha)=\Pr\left\{\Delta\theta\in I_0\left(\alpha;X_{A,t},X_{B,t};X_{A,t}^{*},X_{B,t}^{*}\right)\right\}$ – usually differs from α. It follows that there exists a real number, ϱ_α, such that $\Pr(\varrho_\alpha)=\alpha$. Let $I_0\left(\alpha;X_{A,t}^{*},X_{B,t}^{*};X_{A,t}^{**},X_{B,t}^{**}\right)$ be a version of $I_0\left(\alpha;X_{A,t},X_{B,t};X_{A,t}^{*},X_{B,t}^{*}\right)$ computed using information from $X_{A,t}^{*}$, $X_{B,t}^{*}$, $X_{A,t}^{**}$, and $X_{B,t}^{**}$. $X_{A,t}^{**}$ and $X_{B,t}^{**}$ are resamples with replacement of $X_{A,t}^{*}$ and $X_{B,t}^{*}$. An estimate of $\Pr(\alpha)$ is then

$$\widehat{\Pr}(\alpha)=\Pr\left\{\widehat{\Delta\rho}\in I_0\left(\alpha;X_{A,t}^{*},X_{B,t}^{*};X_{A,t}^{**},X_{B,t}^{**}|X_{A,t},X_{B,t}\right)\right\}. \tag{1}$$

[25] The inverse of λ is the expected block length, $E(L)=\frac{1}{\lambda}$, to be estimated through an inner procedure based on an automatic rule that minimizes the root mean squared error of the bootstrap estimator.

Let N_O^B be the number of bootstrap replications at the outer level of resampling. $\widehat{\Pr}(\alpha)$ is calculated as

$$\widehat{\Pr}(\alpha) = \frac{\sum_{n_O^B=1}^{N_O^B} 1\left\{\widehat{\Delta\rho} \in I_{0,n_O^B}\left(\alpha; X_{A,t}^*, X_{B,t}^*; X_{A,t}^{**}, X_{B,t}^{**}\right)\right\}}{N_O^B}, \tag{2}$$

where $1\{\cdot\}$ is a standard indicator function. Because any useful distributional information on $X_{A,t}^{**}$ and $X_{B,t}^{**}$ given $X_{A,t}^*$ and $X_{B,t}^*$ is unavailable, an inner level of resamples (say, N_I^B resamples for each outer resample, $n_O^B = 1, ..., N_O^B$) from $X_{A,t}^*$ and $X_{B,t}^*$ is used to outline the features of these distributions.[26] The bootstrap estimate for ϱ_α is then the solution, $\widehat{\varrho}_\alpha$, of the equation

$$\widehat{\Pr}(\varrho_\alpha) = \alpha \Longrightarrow \widehat{\varrho}_\alpha = \widehat{\Pr}^{-1}(\alpha).$$

When using discrete variables and discrete bootstrap distributions, an exact solution for this equation cannot always be found unless we use smoothing techniques. We choose the smallest value $\widehat{\varrho}_\alpha$ such that $\widehat{\Pr}(\widehat{\varrho}_\alpha)$ is as close as possible to α – that is, such that $\left|\widehat{\Pr}(\varrho_\alpha) - \alpha\right|$ is minimized over a grid of values and additional conditions defining tolerance are satisfied (see De Pace, 2013, for additional details concerning the algorithm). The iterated bootstrap confidence interval for $\Delta\rho$ is then $I_1\left(\widehat{\varrho}_\alpha; X_{A,t}, X_{B,t}; X_{A,t}^*, X_{B,t}^*\right)$.

Appendix B

The following factor model provides a heuristic framework for the interpretation of the empirical results presented in this paper. Consider M yield spreads as follows: s_t^i with $i = 1, 2, ...M$, for which time series of length T are available, and assume that their dynamics follow, at least as an approximation, the factor structure

$$s_t^i = E_{t-1}\left[s_t^i\right] + \sum_{p=1}^{P} R_t^p \boldsymbol{\beta}_{p,i}' \mathbf{F}_t + \sigma^i \epsilon_t^i, \tag{3}$$

where $\mathbf{F}_t$ is a $K \times 1$ vector of priced, standardized factors (i.e., $E_{t-1}[\mathbf{F}_t] = \mathbf{0}$) with a scalar unit covariance matrix; ϵ_t^i is a white-noise random variable that captures idiosyncratic risks (so that $E_{t-1}[\epsilon_t^i \epsilon_t^j] = 0\ \forall i \neq j$) and is (conditionally and therefore unconditionally) independent of both the factors and the variables describing the state; and R_t^p ($p = 1, 2, ..., P$) is an indicator that captures regime shifts in the factor exposures collected in the $K \times 1$ vector $\boldsymbol{\beta}_{p,i}$. When the state is p, then $R_t^p = 1$ and $R_t^{\text{not } p} = 0$. $E_{t-1}\left[s_t^i\right]$ is the conditional mean of the spread, for instance, determined by imposing no arbitrage restrictions.[27] Given $E_{t-1}\left[s_t^i\right]$, (3) determines the covariance matrix of

[26] Bootstrap samples are drawn using the same nonparametric method in the main and nested bootstraps.

[27] Such conditions are likely to involve the parameters of the regime-switching process unless this process is not priced because the switching risk is completely diversifiable. Given our focus on unconditional correlations dynamics,

the vector collecting the M spreads.

As is customary in the empirical literature on regime-switching regressions, we assume that R_t^p is conditionally uncorrelated with all the factors in $\mathbf{F}_t$, for $p = 1, 2, ..., P$. It follows that all linear influences of the priced risk factors on yield spreads must be captured by $\mathbf{F}_t$ only. In particular, equation (3) implies that, over a given period $[\tau_1, \tau_2]$, the average covariance will be

$$\begin{aligned} Cov[s_t^i, s_t^j; \tau_1, \tau_2] &= E\left\{E_{t-1}\left[\left(\sum_{p=1}^{P} R_t^p \boldsymbol{\beta}_{p,i}' \mathbf{F}_t + \sigma^i \epsilon_t^i\right)\left(\sum_{p=1}^{P} R_t^p \boldsymbol{\beta}_{p,j}' \mathbf{F}_t + \sigma^j \epsilon_t^j\right)\right]; \tau_1, \tau_2\right\} \\ &= \sum_{p=1}^{P} E\left\{E_{t-1}\left[R_t^p\right]; \tau_1, \tau_2\right\} E\left[\boldsymbol{\beta}_{p,i}' \mathbf{F}_t \mathbf{F}_t' \boldsymbol{\beta}_{p,j}\right] = \sum_{p=1}^{P} \bar{\pi}_{\tau_1,\tau_2}^p \boldsymbol{\beta}_{p,i}' \boldsymbol{\beta}_{p,j}, \end{aligned} \tag{4}$$

where term $\bar{\pi}_{\tau_1,\tau_2}^p \equiv E\left[R_t^p; \tau_1, \tau_2\right]$ is the average amount of time that markets spend in regime $p = 1, 2, ..., P$ over the subsample $[\tau_1, \tau_2]$. The factorization of $E_{t-1}\left[\left(R_t^p \boldsymbol{\beta}_{p,i}' \mathbf{F}_t\right)\left(R_t^p \boldsymbol{\beta}_{p,j}' \mathbf{F}_t\right)\right]$ in $E_{t-1}\left[R_t^p\right] E_{t-1}\left[\boldsymbol{\beta}_{p,i}' \mathbf{F}_t \mathbf{F}_t' \boldsymbol{\beta}_{p,j}\right]$ follows from the independence of the regimes from the factors. $E\left[\boldsymbol{\beta}_{p,i}' \mathbf{F}_t \mathbf{F}_t' \boldsymbol{\beta}_{p,j}\right]$ derives instead from the fact that the regime-specific factor exposures are constant within each regime by construction. As a result, the correlation between spreads s_t^i and s_t^j over a given period $[\tau_1, \tau_2]$ is

$$Corr\left[s_t^i, s_t^j; \tau_1, \tau_2\right] = \frac{\sum_{p=1}^{P} \bar{\pi}_{\tau_1,\tau_2}^p \boldsymbol{\beta}_{p,i}' \boldsymbol{\beta}_{p,j}}{\sqrt{\left[\sum_{k=1}^{K} \sum_{p=1}^{P} \bar{\pi}_{\tau_1,\tau_2}^p \beta_{p,ik}^2 + (\sigma^i)^2\right]\left[\sum_{k=1}^{K} \sum_{p=1}^{P} \bar{\pi}_{\tau_1,\tau_2}^p \beta_{p,jk}^2 + (\sigma^j)^2\right]}} \tag{5}$$

for all possible pairs i and j. The presence of a common set of factors, $\mathbf{F}_t$, does not imply that all bivariate correlations will be identical because these will depend on the factor loadings $\boldsymbol{\beta}_{p,i}'$ and $\boldsymbol{\beta}_{p,j}$ in the various states. Moreover, (5) emphasizes that period/regime correlations may change not only if changes in $\bar{\pi}_{\tau_1,\tau_2}^p$ affect the covariance term $\sum_{p=1}^{P} \bar{\pi}_{\tau_1,\tau_2}^p \boldsymbol{\beta}_{p,i}' \boldsymbol{\beta}_{p,j}$, but also if either or both the $[\tau_1, \tau_2]$-period standard deviations in the denominator change, as discussed by Forbes and Rigobon (2002).

Three specific cases are important for our purposes. First, when financial markets are not subject to any regime shifts so that $P = 1$, then

$$Corr\left[s_t^i, s_t^j; \tau_1, \tau_2\right] = \frac{\boldsymbol{\beta}_i' \boldsymbol{\beta}_j}{\sqrt{\left[\sum_{k=1}^{K} \beta_{ik}^2 + (\sigma^i)^2\right]\left[\sum_{k=1}^{K} \beta_{jk}^2 + (\sigma^j)^2\right]}}$$

and all correlations will be constant. In particular, if and only if $\boldsymbol{\beta}_i' \boldsymbol{\beta}_j = 0$, then $Corr\left[s_t^i, s_t^j\right] = 0$; that is, a very special structure of factor loadings must apply for two spread series to be simulta-

this specific aspect is irrelevant for the empirical analysis that follows.

neously uncorrelated.

Second, when there are only two possible recurring regimes (which, for simplicity, we call "good" and "crisis") in the financial markets, then

$$Corr\left[s_t^i, s_t^j; \tau_1, \tau_2\right] = \frac{\bar{\pi}_{\tau_1,\tau_2}^{good}\boldsymbol{\beta}'_{good,i}\boldsymbol{\beta}_{good,j} + \left(1-\bar{\pi}_{\tau_1,\tau_2}^{good}\right)\boldsymbol{\beta}'_{crisis,i}\boldsymbol{\beta}_{crisis,j}}{\sqrt{\Psi}},$$

where

$$\begin{aligned}\Psi \equiv & \left[\bar{\pi}_{\tau_1,\tau_2}^{good}\sum_{k=1}^{K}\beta_{good,ik}^2 + \left(1-\bar{\pi}_{\tau_1,\tau_2}^{good}\right)\sum_{k=1}^{K}\beta_{crisis,ik}^2 + \left(\sigma^i\right)^2\right] \\ & \times\left[\bar{\pi}_{\tau_1,\tau_2}^{good}\sum_{k=1}^{K}\beta_{good,jk}^2 + \left(1-\bar{\pi}_{\tau_1,\tau_2}^{good}\right)\sum_{k=1}^{K}\beta_{crisis,jk}^2 + \left(\sigma^j\right)^2\right]\end{aligned}$$

In this case, $Corr\left[s_t^i, s_t^j; \tau_1, \tau_2\right]$ will increase during crisis periods, when $\bar{\pi}_{\tau_1,\tau_2}^{good}$ declines over the interval $[\tau_1, \tau_2]$, if $\boldsymbol{\beta}'_{crisis,i}\boldsymbol{\beta}_{crisis,j} > \boldsymbol{\beta}'_{good,i}\boldsymbol{\beta}_{good,j}$ more than compensates for possible increases in $\beta_{crisis,ik}^2$ and $\beta_{crisis,jk}^2$ (which means that the common exposures to risk factors increase during a crisis).[28] These considerations obviously extend to the absolute value of $Corr\left[s_t^i, s_t^j; \tau_1, \tau_2\right]$, even though in this case the condition is more generally $\left|\boldsymbol{\beta}'_{crisis,i}\boldsymbol{\beta}_{crisis,j}\right| > \left|\boldsymbol{\beta}'_{good,i}\boldsymbol{\beta}_{good,j}\right|$ to exceed the increase caused by the fact that $\beta_{crisis,ik}^2$ and $\beta_{crisis,jk}^2$ may increase. Under the assumption that the systematic variance is higher in crisis periods, it follows that a higher subperiod absolute value for the correlation coefficient will require $\left|\boldsymbol{\beta}'_{crisis,i}\boldsymbol{\beta}_{crisis,j}\right| > \left|\boldsymbol{\beta}'_{good,i}\boldsymbol{\beta}_{good,j}\right|$.

We can use this factor framework to provide a suggestive heuristic interpretation for our main empirical findings. In Section 4.2, we find strong statistical evidence of nonzero absolute correlations for the large majority of the 55 pairs of spreads investigated in this paper. This result is consistent with the hypothesis that $\boldsymbol{\beta}'_{p,i}\boldsymbol{\beta}_{p,j} \neq 0$ in the heuristic factor model for at least some $p = 1, 2, ..., P$ and for the majority of the spread pairs in the sample. Then it would be interesting to test whether $\boldsymbol{\beta}'_{p,i}\boldsymbol{\beta}_{p,j}$ may be significantly different across alternative regimes, $p = 1, 2, ..., P$. In Section 4.3 our claim that the Great Financial Crisis can be seen as a period of structural change during which correlations between yield spreads are systematically altered suggests the existence of two regimes ($P = 2$, a good vs a crisis state) in the heuristic model. In the good regime, $\left|\boldsymbol{\beta}'_{good,i}\boldsymbol{\beta}_{good,j}\right|$ tends to be low or even approximately zero for most pairs of spreads, i and j. During the crisis regime, however, $\left|\boldsymbol{\beta}'_{crisis,i}\boldsymbol{\beta}_{crisis,j}\right|$ would massively increase, because correlation increases may be obtained only if the change in $\left|\boldsymbol{\beta}'_{crisis,i}\boldsymbol{\beta}_{crisis,j}\right|$ exceeds the variance increase caused by the individual upward shifts in the squared beta exposures, $\beta_{crisis,ik}^2$ and $\beta_{crisis,jk}^2$.

[28] Because this is commonly found in the empirical literature, we are assuming that the systematic spread variance increases during crisis periods. Note that under model (5) idiosyncratic variances are forced to be homoskedastic, in the sense that regime-dependent variation is priced through variations in the betas.

Other results from Sections 4.3 and 4.4 can be mapped into changes in (5). When signs are taken into account, most pairs of correlations lie above the 45-degree line between the pre-crisis and the crisis samples, while the few dots below the no-change line represent modest correlation declines. Through the lens of our heuristic model, this is consistent with $\boldsymbol{\beta}'_{crisis,i}\boldsymbol{\beta}_{crisis,j} \geq 0$ for most pairs but $\boldsymbol{\beta}'_{good,i}\boldsymbol{\beta}_{good,j} < 0$ for a few pairs of spreads. For a large group of 15 to 18 pairs of spreads, however, $\boldsymbol{\beta}'_{good,i}\boldsymbol{\beta}_{good,j} \geq 0$ but $\boldsymbol{\beta}'_{crisis,i}\boldsymbol{\beta}_{crisis,j} > \boldsymbol{\beta}'_{good,i}\boldsymbol{\beta}_{good,j}$.

In Figure 4, we show that (i) almost all "liquidity correlations" increase from the pre-crisis to the Great Financial Crisis subsample and (ii) about half do so in a significant fashion, with weak evidence that such correlations revert to their normal pre-crisis levels in the post-crisis period. We also report that default-risk-related spreads continue to drift upward even after the end of the Great Financial Crisis. On the one hand, these findings suggest that, potentially, two elements of $Corr\left[s^i_t, s^j_t; \tau_1, \tau_2\right]$ are strongly affected (i.e., the ones that possibly capture exposure to liquidity and default risk). On the other hand, they also suggest that more than two regimes might exist in the time evolution of these correlations ($P > 2$). In fact, in the post-crisis period we fail to detect correlation levels comparable to the pre-crisis levels.

Finally, a similar explanation may be applied to a remark in Section 4.4. We show that about half of the correlations directly affected by policy interventions return to correlation levels exceeding the pre-crisis ones. The financial crisis may have determined the insurgence of a novel priced risk factor that not only tilted risk exposures such that $\boldsymbol{\beta}'_{crisis,i}\boldsymbol{\beta}_{crisis,j} > \boldsymbol{\beta}'_{good,i}\boldsymbol{\beta}_{good,j}$ for most pairs of spreads, but also permanently increased such a risk factor.

Policy Measures during the Great Financial Crisis

In this section, we review the main events of the 2007-09 GFC. Our objective is not to exhaustively list all the significant developments or discuss causes and solutions to the crisis.

The financial crisis began with a steep downturn in U.S. residential real estate markets as a growing number of banks and hedge funds reported substantial losses on subprime mortgages and MBS. Even though the crisis had been slowly building since early 2007, the beginning of the spiralling crisis was marked by the August 2007 Fitch Ratings' decision to downgrade one of the major firms that specialized in mortgage intermediation in the subprime segment, Countrywide Financial Corporation. The crisis appeared to be spreading beyond the boundaries of the U.S. mortgage market when it spilled over into the interbank lending market in August 2007. At that time, the LIBOR and other funding rates spiked after the French bank BNP Paribas announced that it would halt redemptions for three of its investment funds.

Initially, the Fed's reaction was limited to calming markets by emphasizing the availability of the discount window. This was achieved by extending the maximum term of discount window loans to 30 days and lowering the federal funds rate target by 50 basis points between August and September 2007. Financial strains eased in September and October 2007 but reappeared in November. In December 2007, the Fed announced the establishment of reciprocal swap currency agreements with the European Central Bank and the Swiss National Bank to provide a source of dollar funding to European financial markets. Also in December, the Fed announced the creation of the Term Auction Facility (TAF) to lend funds directly to banks for a fixed term.[29] Financial markets remained unusually strained in early 2008. In March, the Federal Reserve established the Term Securities Lending Facility (TSLF) to provide secured loans of Treasury securities to primary dealers for 28-day terms. Later in March 2008, the Fed established the Primary Dealer Credit Facility (PDCF) to provide secured overnight loans to primary dealers. In essence, the PDCF opened the discount window to primary government security dealers.[30]

The financial crisis intensified during the final four months of 2008. Lehman Brothers, a major investment bank, filed for bankruptcy on September 15. Lehman's filing triggered widespread withdrawals from money funds heavily invested in the commercial paper issued by major investment banks involved in the U.S. residential market. These occurrences prompted the U.S. Department of the Treasury to announce a temporary program to guarantee investments in participating money market mutual funds, the Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility (ABCPAMLF), which was set up to extend non-recourse loans to U.S. depository institutions and bank holding companies to finance purchases of ABCP from money market mutual funds. Financial markets plunged again in a state of turmoil over the following weeks. On October 7, 2008, the Fed established the Commercial Paper Funding Facility (CPFF) to help alleviate financial strains in the commercial paper market. This facility provided financing for a special purpose vehicle established to purchase 3-month unsecured and asset-backed commercial paper directly from eligible issuers.[31]

Despite these efforts and their beneficial effects on the short-end segment of fixed income markets, the situation remained difficult in most other segments, especially for MBS and associated derivative products (e.g., collateralized debt obligations written on portfolios of MBS). As a result, immense portfolios at several multinational financial institutions remained extremely illiquid and potentially exposed to tremendous losses upon "fire sales." On November 25, the Fed announced the creation of the Term Asset-Backed Securities Lending Facility (TALF). Under this facility, the Federal Reserve Bank of New York provided loans on a non-recourse basis to holders of Aaa-rated

[29] The Fed established the TAF in part because the volume of discount window borrowing had remained low despite the persistent stress in interbank funding markets.

[30] Also in March, the Federal Reserve Board authorized the Federal Reserve Bank of New York to lend $29 billion to a newly created limited liability corporation (Maiden Lane, LLC) to facilitate the acquisition of the distressed investment bank Bear Stearns by JPMorgan Chase.

[31] On October 21, the Fed also introduced the Money Market Investor Funding Facility (MMIFF). Under the MMIFF, the Fed offered to provide loans to a series of special purpose vehicles that purchased assets from money market mutual funds.

asset-backed securities and recently originated consumer and small-business loans. At the same time, the FOMC announced its intention to purchase large amounts of U.S. Treasury securities and MBS issued by Fannie Mae, Freddie Mac, and Ginnie Mae.[32] Between late 2008 and early 2009 the financial crisis remained at the forefront of policy concerns, as witnessed by the Federal Reserve Board's approval of the applications by several large financial firms to become bank holding companies. In February 2009, the Fed announced the extension of all the existing liquidity programs; in March 2009, the U.S. Treasury and the Fed announced the effective launch of the TALF with its first auctions. In May 2009, the Fed announced that CMBS would become eligible collateral under the TALF.

The turnaround and the exit from the crisis appear to have occurred – we can now claim in hindsight – between the late spring and fall of 2009. In fact, while in June 2009 the Fed had further announced to a number of extensions and modifications to several of its liquidity programs, a novel desire to fine-tune the programs had replaced the tension toward expanding them, which had dominated policymaking until April 2009.[33] In November 2009, with the situation rapidly improving and short-term debt (especially interbank) markets experiencing a thawing cycle counter to the severe, paralyzing disruptions in September-November 2008, the Fed approved a first reduction in the maximum maturity of credit at the discount window. This represented the first official acknowledgment that the financial system was healing and the crisis was possibly over. This was made evident not only by the Fed but by all central banks around the world when, between late 2009 and early 2010, they all terminated some or most of the public support measures introduced in response to the financial crisis. On the demand side, the take-up of many measures drastically declined around the turn of the year. In February 2010, a number of liquidity programs (CPFF, ABCPAMLF, TSLF) expired and were not replaced by the Fed. The figure in Table C.3 plots the time series of the total adjusted monetary base (as defined by the St. Louis Fed) and the total amount of the outstanding loans under all liquidity/credit facilities between 2008 and 2011. The total amount of the credit extended through all liquidity facilities begins at the end of 2008 and peaks after 14 to 15 months in March 2009. Then the amount starts to decline, and the speed of descent becomes noticeable after June 2009. The monetary base continued to grow throughout 2009, with a stabilization around late 2009 as the initial asset purchase programs rolled toward their ends.

[32]The Federal Open Market Committee (FOMC) would later increase the amount of its purchases in 2009. This program has come to be referred to as "quantitative easing" (QE). In addition to the Fed's rescue operations and programs to stabilize specific financial markets, the FOMC reduced its target for the federal funds rate from 5.25 percent in August 2007 to a range of 0 to 0.25 percent in December 2008.

[33]For instance, the Fed announced that the amount of funds auctioned at the biweekly TAF auctions would be reduced from $150 billion to $125 billion, effective with the July 13, 2009, auction.

Table 1
Definition of Spreads Used in the Analysis and Classification

	Spread (i)	Liquidity (ii)	Default (iii)	Policy programs (iii)	Short term (iv)	Notes
S1	3-mo LIBOR – OIS	YES	NO	YES	YES	Standard indicator of the liquidity premium of widespread use; possibly affected by swap arrangements among central banks. See Christensen et al. (2010), Manconi et al. (2012), and Hu et al. (2013).
S2	3-mo Aa Fin. CP – T-bill	YES	YES	YES	YES	Representative of the default risk of the financial sector, possibly affected by repo run; also influenced by specific programs (Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility, Commercial Paper Funding Facility, and Term Asset-Backed Securities Lending Facility). See Adrian et al. (2010).
S3	3-mo ABCP – T-bill	YES	YES	YES	YES	Credit and liquidity premium-affected spread at the core of the financial crisis and affected by Term Asset-Backed Securities Lending Facility/Term Auction Facility. See Wu and Zhang (2008), and Adrian et al. (2010).
S4	1-yr Aaa ARM – T-bill	NO	YES	NO	YES	Representative of subprime rates charged on innovative mortgage contracts. See Krainer (2010).
S5	5-yr Interest rate swap – Treasury	NO	YES	NO	NO	Indicator of default risk premia in the financial sector (because swap contracts carry counterparty risk). See Liu et al. (2006).
S6	5-yr REFcorp – Treasury	YES	NO	YES	NO	Indicator of liquidity risk premium (as it contains no differential default risk by construction); affected by Term Asset-Backed Securities Lending Facility programs although indirectly. See Hu et al. (2013) and Longstaff (2004).
S7	5-yr Aaa private label CMBS – Treasury	YES	YES	NO	NO	Represents the risk-premium on private-label securitized mortgages often blamed as the root of the real estate crisis; not directly affected by QE. See Nichols and Cunningham (2009) and Campbell et al. (2011).
S8	10-yr Off-the-Run – On-the-Run Treasury	YES	NO	YES	NO	Indicator of liquidity premium; possibly affected by QE but unclear how. See Fleming (2003).
S9	20-yr Moody's Baa – Aaa	NO	YES	NO	NO	Corporate default spread; never directly affected by QE or other liquidity programs. See Guidolin and Tam (2010), Longstaff (2010), and Hu et al. (2013).
S10	20-yr Junk spread - Corporate Bbb – Aa	NO	YES	NO	NO	Corporate default spread; rarely directly affected by policy interventions.
S11	30-yr Freddie Mac conventional fixed rate mortgage – Treasury	NO	YES	YES	NO	Represents the premium on agency MBS; as such affected by LSAP/QE. See Walentin (2013) and Stroebel and Taylor (2012).

Note: This table lists the 11 spreads (S1-S11) used in the analysis. Classification (by column): (i) spread is a proxy of liquidity risk premium; (ii) spread is a proxy of default risk premium; (iii) spread has been affected by active policy programs; (iv) spreads refers to either short (1-year average time to maturity or less) or long term fixed income markets.

Table 2
Summary Statistics for Yield Spreads: Common Pre-Crisis, Crisis, and Post-Crisis Sample Periods

Pre-Crisis Period (September 2002–July 2007)

Spread	Weekly Obs.	Mean	Median	St. Dev.	Interq. Range	Skewness	Excess Kurtosis
S1) 3-mo LIBOR–OIS	253	0.106	0.098	0.045	0.057	0.983	2.109
		(0.000)	(0.000)			(0.031)	(0.121)
S2) 3-mo Aa Fin. CP–T-bill	253	0.157	0.130	0.099	0.120	1.285	1.838
		(0.000)	(0.000)			(0.002)	(0.252)
S3) 3-mo ABCP–T-bill	253	0.190	0.170	0.098	0.120	1.265	1.728
		(0.000)	(0.000)			(0.002)	(0.130)
S4) 1-yr Aaa ARM–T-bill	253	1.453	1.030	0.847	1.770	0.219	-1.709
		(0.000)	(0.000)			(0.011)	(0.000)
S5) 5-yr Interest rate swap–Treasury	253	0.440	0.440	0.095	0.130	-0.287	0.385
		(0.000)	(0.000)			(0.296)	(0.000)
S6) 5-yr REFcorp–Treasury	253	0.088	0.075	0.106	0.150	0.425	-0.131
		(0.000)	(0.000)			(0.061)	(0.000)
S7) 5-yr Aaa private label CMBS–Treasury	253	0.764	0.720	0.153	0.170	1.270	1.432
		(0.000)	(0.000)			(0.000)	(0.077)
S8) 10-yr Off-the-Run-On-the-Run–Treasury	253	0.148	0.129	0.114	0.136	0.892	1.444
		(0.000)	(0.000)			(0.026)	(0.185)
S9) 20-yr Moody's Baa–Aaa	253	0.977	0.930	0.207	0.273	0.504	-0.616
		(0.000)	(0.000)			(0.001)	(0.010)
S10) 20-yr Junk spread– Corporate Bbb-Aa	253	0.705	0.610	0.208	0.211	1.815	3.225
		(0.000)	(0.000)			(0.000)	(0.000)
S11) Freddie Mac 30-yr conventional fixed rate mortgage–Treasury	253	1.115	1.125	0.360	0.673	-0.009	-1.442
		(0.000)	(0.000)			(0.932)	(0.000)

Crisis Period (August 2007–June 2009)

Spread	Weekly Obs.	Mean	Median	St. Dev.	Interq. Range	Skewness	Excess Kurtosis
S1) 3-mo LIBOR–OIS	100	0.944	0.776	0.589	0.310	2.414	6.318
		(0.000)	(0.000)			(0.038)	(0.089)
S2) 3-mo Aa Fin. CP–T-bill	100	1.020	0.985	0.625	0.915	0.994	1.397
		(0.000)	(0.000)			(0.107)	(0.250)
S3) 3-mo ABCP–T-bill	100	1.255	1.075	0.846	1.040	1.344	2.169
		(0.000)	(0.000)			(0.060)	(0.192)
S4) 1-yr Aaa ARM–T-bill	100	3.220	3.245	1.034	1.780	-0.495	-0.828
		(0.000)	(0.000)			(0.057)	(0.149)
S5) 5-yr Interest rate swap–Treasury	100	0.774	0.745	0.201	0.280	0.239	0.111
		(0.000)	(0.000)			(0.554)	(0.000)
S6) 5-yr REFcorp–Treasury	100	0.589	0.478	0.458	0.770	0.506	-0.930
		(0.000)	(0.000)			(0.042)	(0.000)
S7) 5-yr Aaa private label CMBS–Treasury	100	5.652	3.715	4.459	6.820	0.879	-0.635
		(0.000)	(0.000)			(0.003)	(0.136)
S8) 10-yr Off-the-Run-On-the-Run–Treasury	100	0.265	0.230	0.192	0.236	0.791	-0.031
		(0.000)	(0.000)			(0.031)	(0.909)
S9) 20-yr Moody's Baa–Aaa	100	1.842	1.470	0.854	1.568	0.543	-1.242
		(0.000)	(0.000)			(0.006)	(0.000)
S10) 20-yr Junk spread– Corporate Bbb-Aa	100	1.279	0.910	0.800	1.610	0.841	-1.017
		(0.000)	(0.000)			(0.000)	(0.000)
S11) Freddie Mac 30-yr conventional fixed rate mortgage–Treasury	100	1.601	1.600	0.401	0.405	-0.328	0.754
		(0.000)	(0.000)			(0.461)	(0.250)

Post-Crisis Period (July 2009–December 2011)

Spread	Weekly Obs.	Mean	Median	St. Dev.	Interq. Range	Skewness	Excess Kurtosis
S1) 3-mo LIBOR–OIS	131	0.188	0.149	0.104	0.118	1.113	0.341
		(0.000)	(0.000)			(0.006)	(0.826)
S2) 3-mo Aa Fin. CP–T-bill	131	0.148	0.130	0.062	0.030	1.715	2.983
		(0.000)	(0.000)			(0.306)	(0.323)
S3) 3-mo ABCP–T-bill	131	0.215	0.200	0.074	0.040	1.296	2.292
		(0.000)	(0.000)			(0.852)	(0.377)
S4) 1-yr Aaa ARM–T-bill	131	3.502	3.450	0.452	0.740	0.230	-0.984
		(0.000)	(0.000)			(0.239)	(0.000)
S5) 5-yr Interest rate swap–Treasury	131	0.276	0.270	0.085	0.120	0.446	0.212
		(0.000)	(0.000)			(0.248)	(0.000)
S6) 5-yr REFcorp–Treasury	131	0.562	0.612	0.172	0.301	-0.086	-1.179
		(0.000)	(0.000)			(0.641)	(0.000)
S7) 5-yr Aaa private label CMBS–Treasury	131	3.188	2.830	0.876	1.050	2.209	6.393
		(0.000)	(0.000)			(0.151)	(0.243)
S8) 10-yr Off-the-Run-On-the-Run–Treasury	131	0.135	0.123	0.096	0.132	0.650	0.060
		(0.000)	(0.000)			(0.729)	(0.039)
S9) 20-yr Moody's Baa–Aaa	131	1.105	1.070	0.205	0.200	0.079	1.158
		(0.000)	(0.000)			(0.006)	(0.000)
S10) 20-yr Junk spread– Corporate Bbb-Aa	131	1.006	0.910	0.338	0.190	1.616	2.597
		(0.000)	(0.000)			(0.012)	(0.000)
S11) Freddie Mac 30-yr conventional fixed rate mortgage–Treasury	131	0.531	0.490	0.254	0.360	0.445	-1.442
		(0.000)	(0.000)			(0.926)	(0.001)

Note: Yield spreads are expressed in percentage, annualized basis points. In parenthesis, the p-value for the median refers to a Wilcoxon signed rank test.

Table 3
Cross-Section Correlations over Sample Periods

Pre-Crisis (09/27/2002–07/27/2007)

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S2	-0.352									
S3	-0.417	0.978								
S4	0.693	-0.600	-0.586							
S5	-0.395	0.298	0.315	-0.354						
S6	0.113	-0.255	-0.268	0.358	0.341					
S7	0.453	-0.122	-0.130	0.514	0.173	0.191				
S8	0.304	-0.401	-0.369	0.576	0.397	0.618	0.504			
S9	0.598	-0.165	-0.220	0.443	-0.029	0.268	0.649	0.475		
S10	0.582	-0.321	-0.332	0.580	-0.211	0.127	0.497	0.493	0.678	
S11	-0.517	0.602	0.569	-0.899	0.390	-0.410	-0.231	-0.478	-0.126	-0.383

Mean of absolute correlations: 0.406 St. dev. of absolute correlations: 0.196

Crisis (08/03/2007–06/26/2009)

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S2	0.625									
S3	0.620	0.920								
S4	0.357	-0.210	-0.247							
S5	0.466	0.689	0.654	-0.049						
S6	0.434	-0.169	-0.193	0.841	0.038					
S7	0.355	-0.297	-0.311	0.833	-0.196	0.901				
S8	0.501	-0.051	-0.096	0.746	0.138	0.888	0.779			
S9	0.502	-0.208	-0.217	0.866	-0.076	0.923	0.945	0.846		
S10	0.002	-0.614	-0.594	0.778	-0.472	0.774	0.831	0.633	0.790	
S11	0.501	0.452	0.387	-0.049	0.455	0.152	0.120	0.135	0.153	-0.342

Mean of absolute correlations: 0.462 St. dev. of absolute correlations: 0.296

Post-Crisis (07/03/2009–12/30/2011)

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S2	0.504									
S3	0.748	0.712								
S4	-0.335	-0.142	-0.425							
S5	0.448	0.097	0.220	0.151						
S6	0.161	0.200	0.103	0.461	0.647					
S7	0.233	-0.043	-0.052	0.619	0.617	0.604				
S8	-0.044	-0.092	-0.192	0.545	0.540	0.600	0.620			
S9	0.653	0.293	0.384	0.233	0.543	0.447	0.638	0.433		
S10	0.034	-0.156	-0.249	0.825	0.447	0.507	0.856	0.654	0.594	
S11	0.667	0.271	0.439	0.024	0.586	0.539	0.552	0.267	0.708	0.331

Mean of absolute correlations: 0.409 St. dev. of absolute correlations: 0.231

Note: The table reports the correlation coefficients between 11 fixed income yield spreads over three sample periods.

Table 4
Ng's Uniform Spacings Test of Zero Cross-Section Correlation (11 Spreads)

Sample Period	Pairs	% (θ)	Positive Corr.	Negative Corr.	q=2 SVR	q=2 Prob.	q=4 SVR	q=4 Prob.	q=6 SVR	q=6 Prob.
Pre-Crisis	55	100.00	30	25	**-3.197**	0.001	**-2.705**	0.007	**-2.229**	0.026
Crisis	55	100.00	37	18	1.295	0.195	**1.829**	0.067	**3.049**	0.002
Post-Crisis	55	100.00	45	10	**2.565**	0.010	**4.105**	0.000	**4.732**	0.000

First Split

	Low Absolute Correlation Set										**High Absolute Correlation Set**									
Sample Period	Pairs	% (θ)	Positive Corr.	Negative Corr.	q=2 SVR	q=2 Prob.	q=4 SVR	q=4 Prob.	q=6 SVR	q=6 Prob.	Pairs	% (1-θ)	Positive Corr.	Negative Corr.	q=2 SVR	q=2 Prob.	q=4 SVR	q=4 Prob.	q=6 SVR	q=6 Prob.
Pre-Crisis	6	10.91	2	4	-0.195	0.845	0.234	0.815	---	---	49	9.89	28	21	**4.336**	0.000	1.209	0.227	0.149	0.882
Crisis	7	12.73	2	5	0.433	0.665	-1.193	0.233	-1.070	0.285	48	87.27	35	13	1.445	0.149	**3.448**	0.001	**4.335**	0.000
Post-Crisis	8	14.55	4	4	0.515	0.607	-0.978	0.328	-1.048	0.295	47	85.45	41	6	**2.623**	0.009	**4.808**	0.000	**3.505**	0.000

Note: The table reports the results of spacings tests of zero cross-section correlation for 11 yield spreads. The parameter θ that partitions the N=55 absolute sample correlations into two groups (low absolute correlation sets and high absolute correlations set) is estimated by maximum likelihood. The null of zero cross-section correlation within each group (including the original, full sample of 55 correlations) is tested using a standardized SVR test. Figures in bold indicate rejection of the null. Sample periods: Pre-Crisis: 09/27/2002–07/27/2007; Crisis: 08/03/2007–06/26/2009; Post-Crisis: 07/03/2009–12/30/2011. SVR statistics in bold indicate rejection of the null hypothesis.

Table 5
Bootstrap-Based Breakpoint Tests in Pairwise Correlation Coefficients

Panel A. Breakdate: Week of July 27, 2007

Correlation Changes between Pre-Crisis and Crisis Periods

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S2	**0.977**									
S3	**1.038**	-0.058								
S4	**-0.336**	0.391	0.339							
S5	**0.861**	**0.391**	**0.338**	0.304						
S6	0.322	0.086	0.075	**0.484**	-0.302					
S7	-0.098	-0.175	-0.181	**0.318**	**-0.369**	**0.710**				
S8	0.197	0.349	0.274	**0.169**	-0.259	**0.270**	**0.275**			
S9	-0.097	-0.044	0.002	**0.423**	-0.048	**0.655**	**0.296**	**0.371**		
S10	**-0.579**	**-0.292**	-0.262	0.198	-0.262	**0.647**	**0.334**	0.140	0.112	
S11	**1.018**	-0.150	-0.182	**0.850**	0.065	**0.562**	0.351	**0.613**	0.279	0.041

Sign and Significance of the Correlation Changes between Pre-Crisis and Crisis Periods

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S2	**U**									
S3	**U**	d								
S4	**D**	u	u							
S5	**U**	**U**	**U**	u						
S6	u	u	u	**U**	d					
S7	d	d	d	**U**	**D**	**U**				
S8	u	u	u	**U**	d	**U**	**U**			
S9	d	d	u	**U**	d	**U**	**U**	**U**		
S10	**D**	**D**	d	u	d	**U**	**U**	u	u	
S11	**U**	d	d	**U**	u	**U**	u	**U**	u	u

Summary of Correlation Changes

	Total	Share		Significant	Share
No. of Pairs	55			25	
u+**U**	38	69.09%	**U**	21	84.00%
d+**D**	17	30.91%	**D**	4	16.00%

Liquidity Problems?

	Count	Share		Significant	Share
YY	15			5	
u+**U**	11	73.33%	**U**	5	100.00%
d+**D**	4	26.67%	**D**	0	0.00%
NN	10			2	
u+**U**	8	80.00%	**U**	2	100.00%
d+**D**	2	20.00%	**D**	0	0.00%

Default Problems?

	Count	Share		Significant	Share
YY	28			9	
u+**U**	17	60.71%	**U**	7	77.78%
d+**D**	11	39.29%	**D**	2	22.22%
NN	3			1	
u+**U**	3	100.00%	**U**	1	100.00%
d+**D**	0	0.00%	**D**	0	0.00%

Policy Intervention?

	Count	Share		Significant	Share
YY	15			6	
u+**U**	12	80.00%	**U**	6	100.00%
d+**D**	3	20.00%	**D**	0	0.00%
NN	10			5	
u+**U**	7	70.00%	**U**	4	80.00%
d+**D**	3	30.00%	**D**	1	20.00%

Short/Long?

	Count	Share		Significant	Share
LL	21			11	
u+**U**	16	76.19%	**U**	10	90.91%
d+**D**	5	23.81%	**D**	1	9.09%
SS	6			3	
u+**U**	4	66.67%	**U**	2	66.67%
d+**D**	2	33.33%	**D**	1	33.33%

Panel B. Breakdate: Week of June 26, 2009

Correlation Changes between Crisis and Post-Crisis Periods

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S2	-0.121									
S3	0.128	-0.208								
S4	**-0.692**	0.068	-0.179							
S5	-0.018	**-0.592**	**-0.433**	0.201						
S6	-0.274	0.369	0.296	**-0.381**	**0.608**					
S7	-0.122	0.255	0.259	**-0.214**	**0.813**	**-0.297**				
S8	**-0.545**	-0.041	-0.096	**-0.201**	0.402	**-0.288**	-0.160			
S9	0.151	**0.502**	**0.602**	**-0.633**	**0.619**	**-0.476**	**-0.307**	**-0.414**		
S10	0.032	**0.458**	**0.345**	0.047	**0.920**	-0.267	0.025	0.021	-0.196	
S11	0.166	-0.181	0.051	0.073	0.131	0.388	0.432	0.132	0.555	0.673

Sign and Significance of the Correlation Changes between Crisis and Post-Crisis Periods

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S2	d									
S3	u	d								
S4	**D**	u	d							
S5	d	**D**	**D**	u						
S6	d	u	u	**D**	**U**					
S7	d	u	u	**D**	**U**	**D**				
S8	**D**	d	d	**D**	u	**D**	d			
S9	u	**U**	**U**	**D**	**U**	**D**	**D**	**D**		
S10	u	**U**	**U**	u	**U**	d	u	u	d	
S11	u	d	u	u	u	u	u	u	u	u

Summary of Correlation Changes

	Total	Share		Significant	Share
No. of Pairs	55			21	
u+**U**	30	54.55%	**U**	8	38.10%
d+**D**	25	45.45%	**D**	13	61.90%

Liquidity Problems?

	Count			Significant	
YY	15			3	
u+**U**	5	33.33%	**U**	0	0.00%
d+**D**	10	66.67%	**D**	3	100.00%
NN	10			3	
u+**U**	8	80.00%	**U**	2	66.67%
d+**D**	2	20.00%	**D**	1	33.33%

Default Problems?

	Count	Share		Significant	Share
YY	28			12	
u+**U**	19	67.86%	**U**	7	58.33%
d+**D**	9	32.14%	**D**	5	41.67%
NN	3			2	
u+**U**	0	0.00%	**U**	0	0.00%
d+**D**	3	100.00%	**D**	2	100.00%

Policy Intervention?

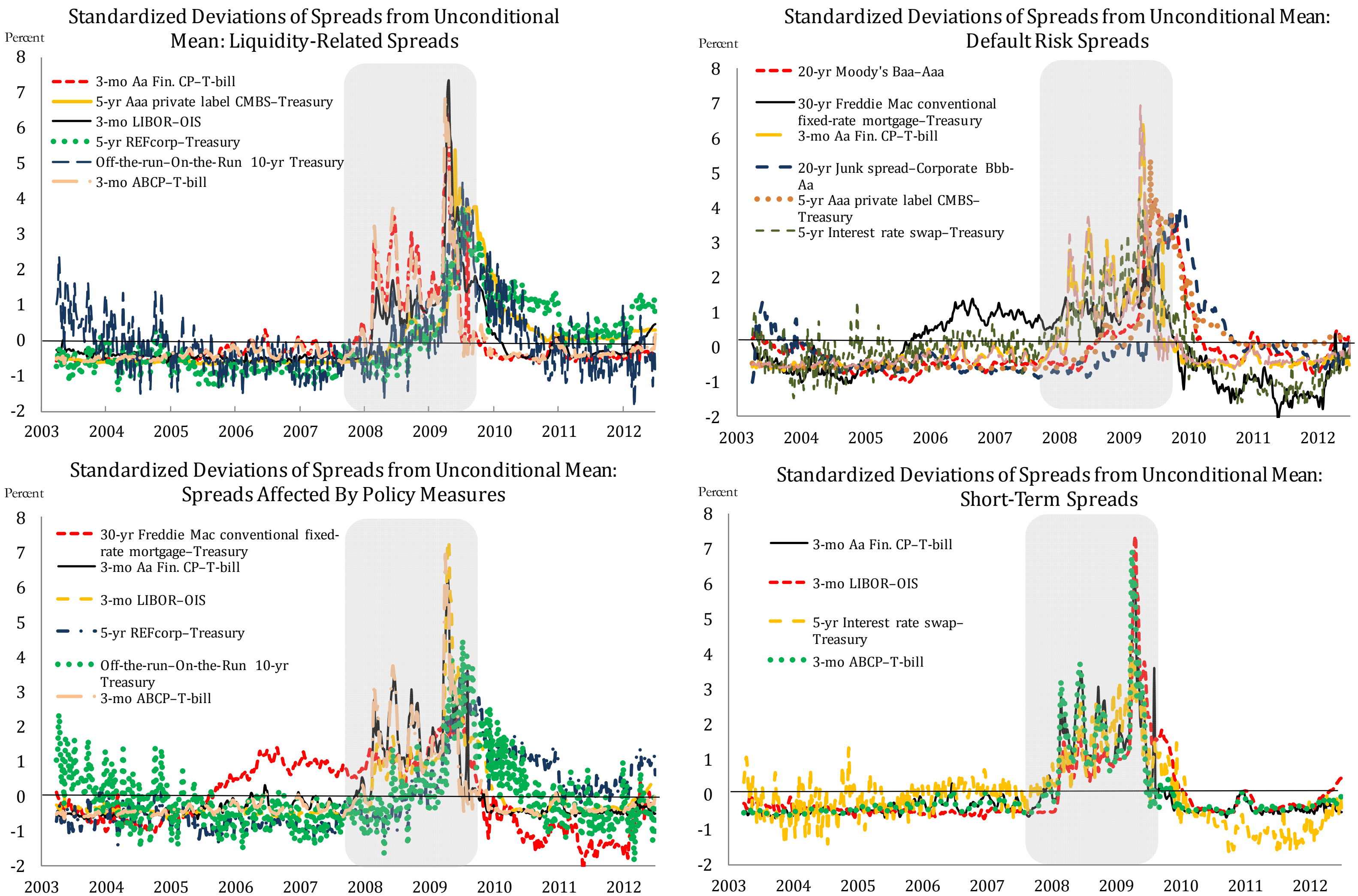
	Count	Share		Significant	Share
YY	15			2	
u+**U**	7	46.67%	**U**	0	0.00%
d+**D**	8	53.33%	**D**	2	100.00%
NN	10			6	
u+**U**	6	60.00%	**U**	3	50.00%
d+**D**	4	40.00%	**D**	3	50.00%

Short/Long?

	Count	Share		Significant	Share
LL	21			9	
u+**U**	13	61.90%	**U**	4	44.44%
d+**D**	8	38.10%	**D**	5	55.56%
SS	6			1	
u+**U**	2	33.33%	**U**	0	0.00%
d+**D**	4	66.67%	**D**	1	100.00%

Note: The table reports the results of nonparametric bootstrap breakpoint tests in the (signed) pairwise correlations between spreads. The breakpoints are exogenously given and correspond to those isolated in Section 4 (i.e., the weeks ending on July 27, 2007 and on June 26, 2009). Shifts are considered statistically significant when the null hypothesis of no change in correspondence of the break is rejected with a p-value of 10% or lower (in boldface). u: positive change; n: negative change; **U**: significantly positive change; **D**: significantly negative change. YY (NN): Both series are (not) characterized by liquidity, default risk, policy intervention, or maturity effects.

Figure 1
Plots of Yield Spreads Classified on the Basis of Their Nature and Policy Effects



Note: The shaded areas indicate the Great Financial Crisis period.

Figure 2
Dynamics of Ordered Absolute Correlations between Sample Periods

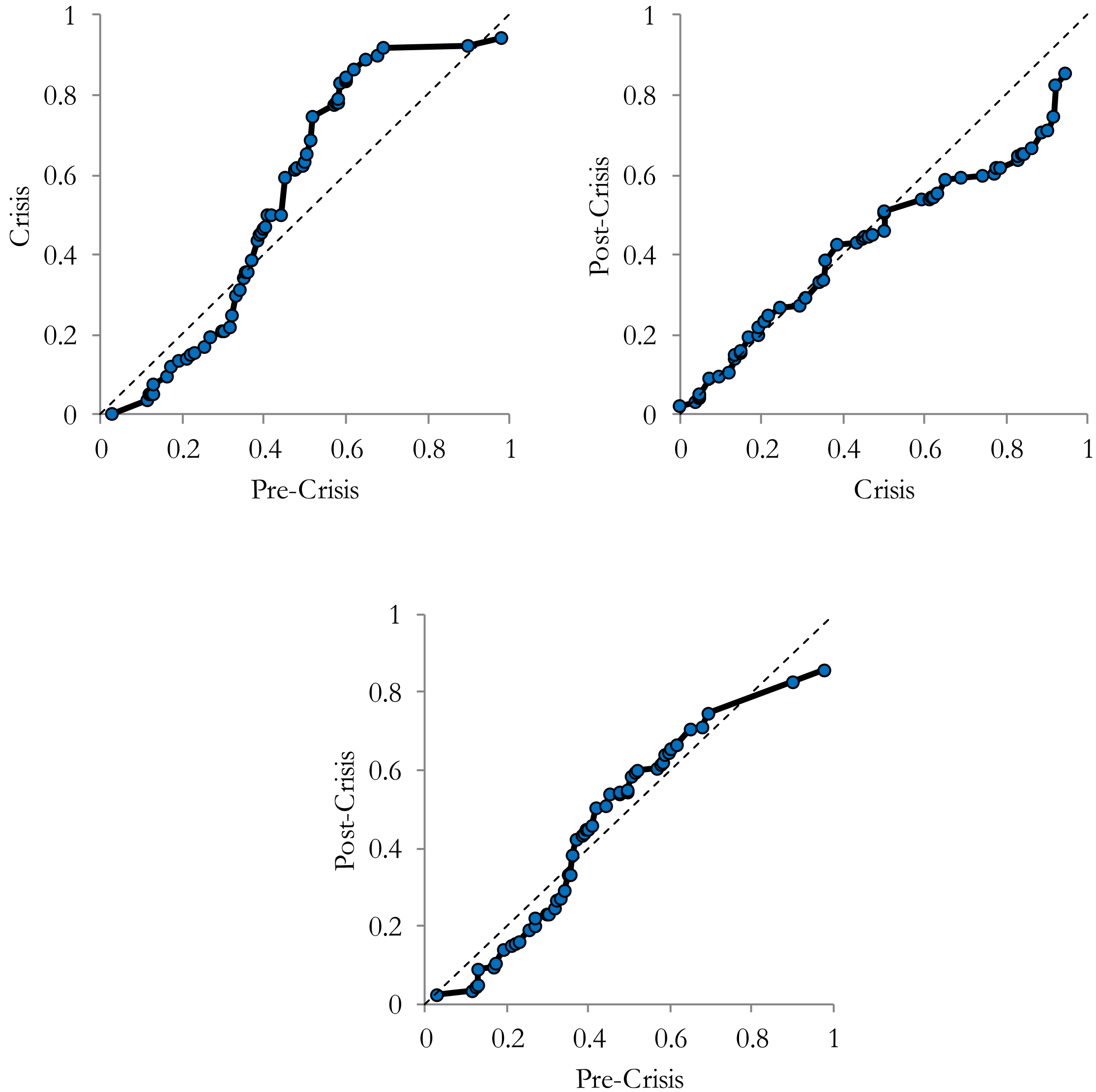
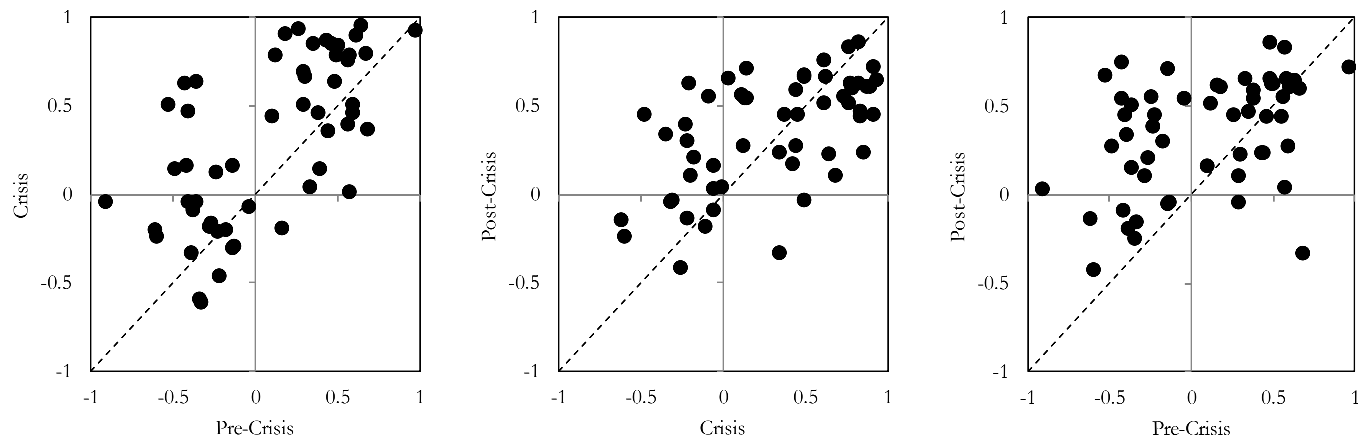


Figure 3
Dynamics of Signed Correlations between Sample Periods

All Changes



Only Statistically Significant Correlation Changes

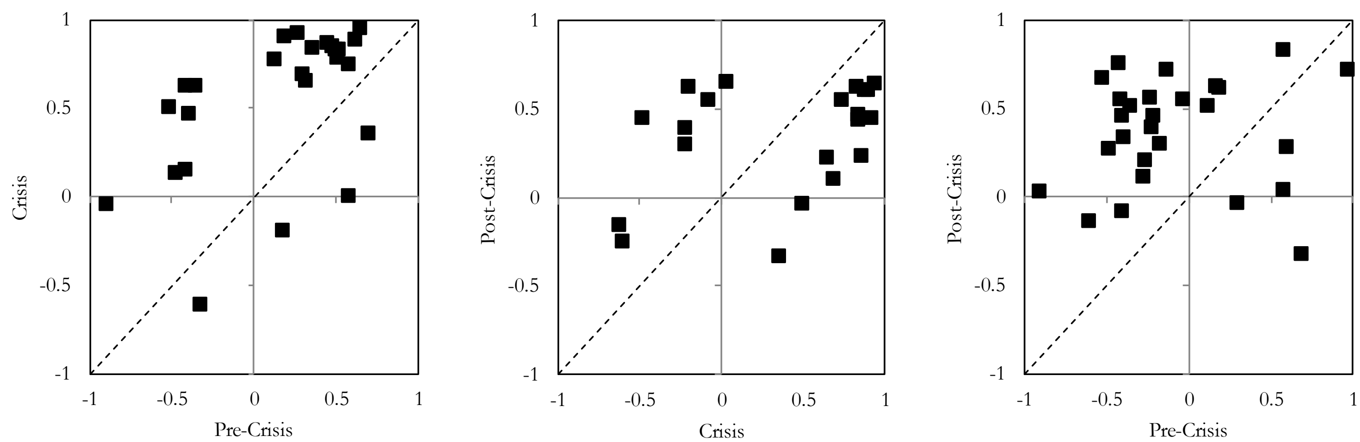
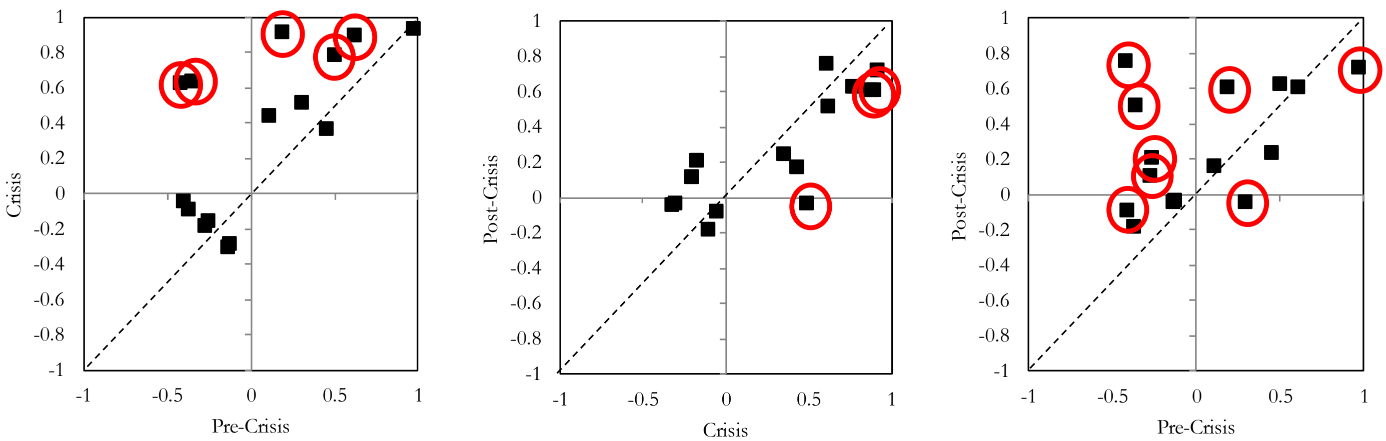
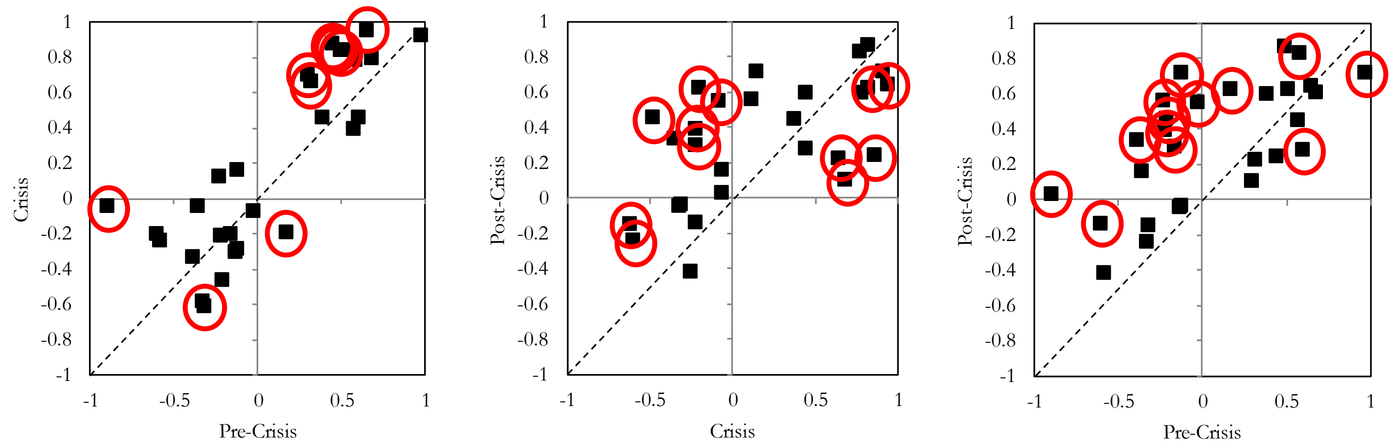


Figure 4
Dynamics of Signed Correlations between Sample Periods

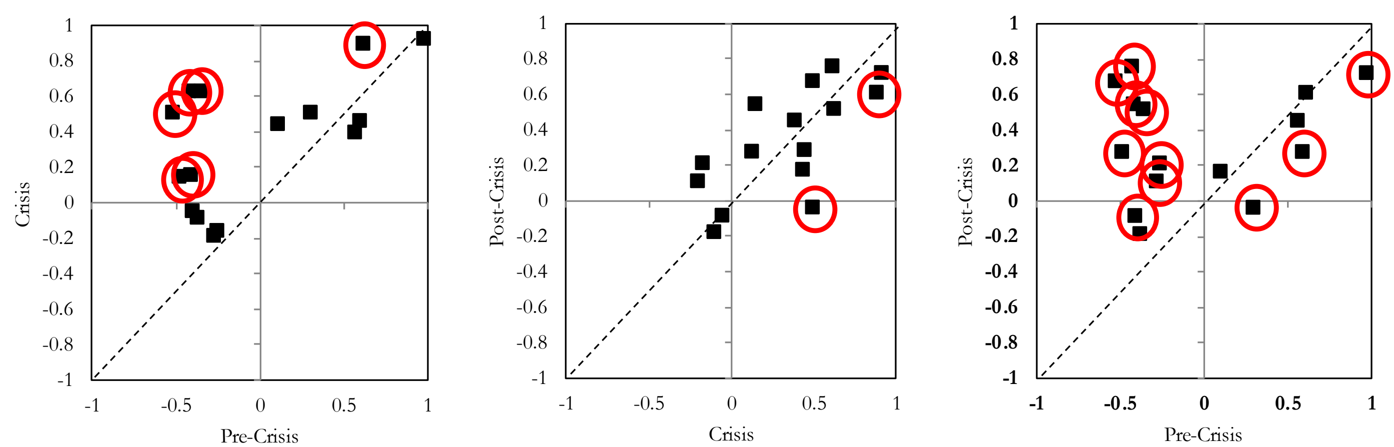
Liquidity Spread Pairs



Default Risk Spread Pairs



Spread Pairs Affected by Policy Intervention

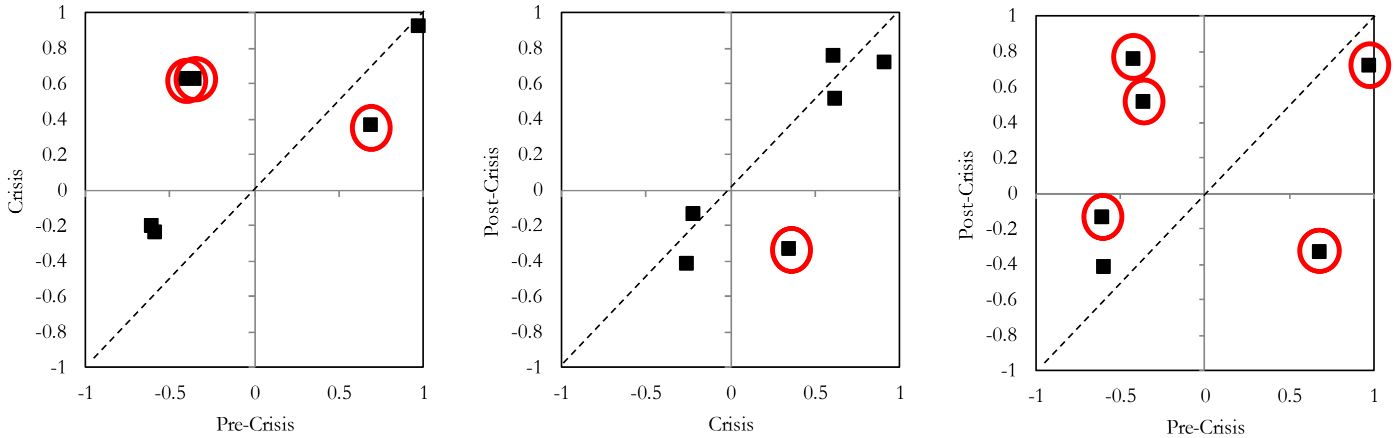


Note: Significant correlation changes are circled.

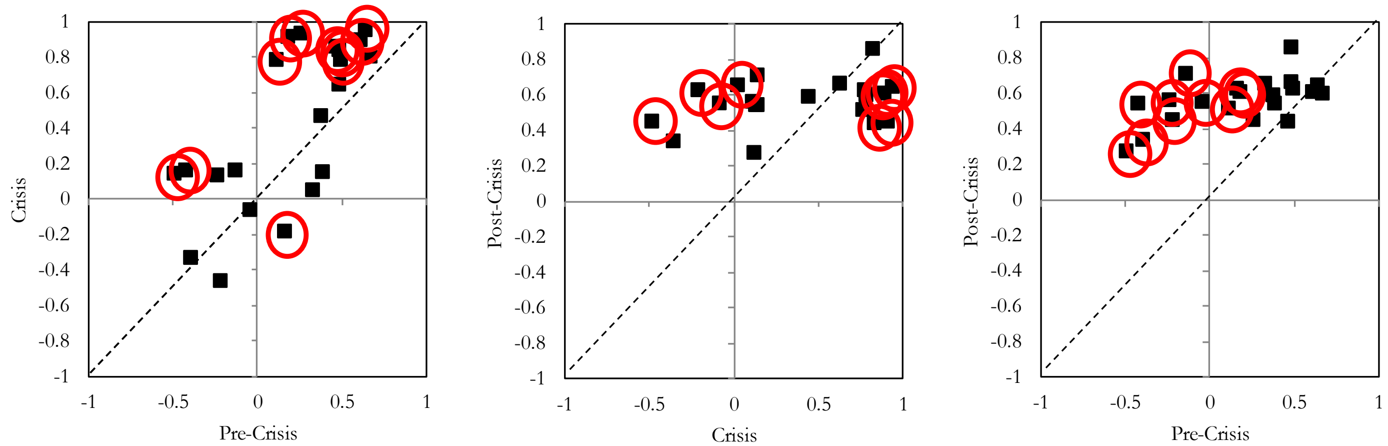
Figure 5

Dynamics of Signed Correlations between Sample Periods: Spread Pairs by Maturity

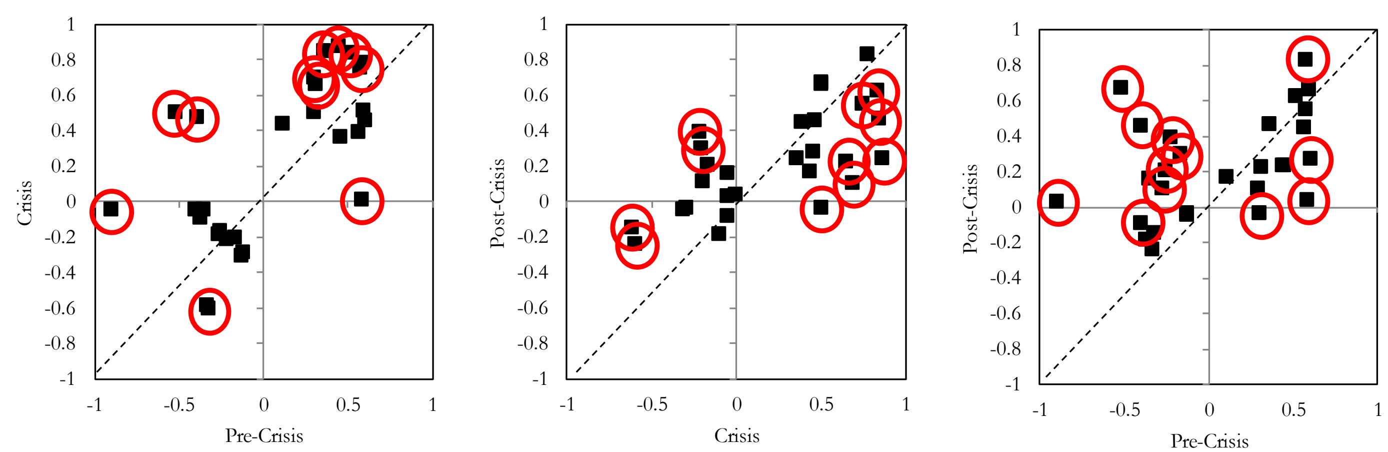
Short-Term Maturity Spreads



Long-Term Maturity Spreads



Short- and Long-Term Maturity Spreads



Note: Significant correlation changes are circled.

Appendix C

Table C1. List of Pairwise Correlations as Split by Ng's Spacings Methodology

	Pre-Crisis			Crisis			Post Crisis		
Low Absolute Correlation Set	S9	S5	-0.029	S9	S5	-0.076	S11	S4	0.024
	S1	S6	0.113	S1	S10	0.002	S1	S10	0.034
	S7	S2	-0.122	S6	S5	0.038	S7	S2	-0.043
	S7	S3	-0.13	S11	S4	-0.049	S1	S8	-0.044
	S9	S11	-0.126	S8	S2	-0.051	S7	S3	-0.052
	S6	S10	0.127	S4	S5	-0.049	S8	S2	-0.092
				S8	S3	-0.096	S2	S5	0.097
							S6	S3	0.103
High Absolute Correlation Set	S9	S2	-0.165	S11	S7	0.12	S4	S2	-0.142
	S7	S5	0.173	S11	S8	0.135	S4	S5	0.151
	S7	S6	0.191	S8	S5	0.138	S2	S10	-0.156
	S10	S5	-0.211	S11	S6	0.152	S1	S6	0.161
	S9	S3	-0.22	S9	S11	0.153	S8	S3	-0.192
	S11	S7	-0.231	S6	S2	-0.169	S6	S2	0.2
	S6	S2	-0.255	S6	S3	-0.193	S3	S5	0.22
	S9	S6	0.268	S7	S5	-0.196	S7	S1	0.233
	S6	S3	-0.268	S9	S2	-0.208	S9	S4	0.233
	S2	S5	0.298	S4	S2	-0.21	S3	S10	-0.249
	S1	S8	0.304	S9	S3	-0.217	S11	S8	0.267
	S3	S5	0.315	S4	S3	-0.247	S11	S2	0.271
	S2	S10	-0.321	S7	S2	-0.297	S9	S2	0.293
	S3	S10	-0.332	S7	S3	-0.311	S11	S10	0.331
	S6	S5	0.341	S11	S10	-0.342	S4	S1	-0.335
	S1	S2	-0.352	S7	S1	0.355	S9	S3	0.384
	S4	S5	-0.354	S4	S1	0.357	S4	S3	-0.425
	S4	S6	0.358	S11	S3	0.387	S9	S8	0.433
	S8	S3	-0.369	S1	S6	0.434	S11	S3	0.439
	S11	S10	-0.383	S11	S2	0.452	S9	S6	0.447
	S11	S5	0.39	S11	S5	0.455	S10	S5	0.447
	S1	S5	-0.395	S1	S5	0.466	S1	S5	0.448
	S8	S5	0.397	S10	S5	-0.472	S4	S6	0.461
	S8	S2	-0.401	S11	S1	0.501	S1	S2	0.504
	S11	S6	-0.41	S1	S8	0.501	S6	S10	0.507
	S1	S3	-0.417	S9	S1	0.502	S11	S6	0.539
	S9	S4	0.443	S3	S10	-0.594	S8	S5	0.54
	S7	S1	0.453	S2	S10	-0.614	S9	S5	0.543
	S9	S8	0.475	S1	S3	0.62	S4	S8	0.545
	S11	S8	-0.478	S1	S2	0.625	S11	S7	0.552
	S8	S10	0.493	S8	S10	0.633	S11	S5	0.586
	S7	S10	0.497	S3	S5	0.654	S9	S10	0.594
	S7	S8	0.504	S2	S5	0.689	S6	S8	0.6
	S4	S7	0.514	S4	S8	0.746	S7	S6	0.604
	S11	S1	-0.517	S6	S10	0.774	S7	S5	0.617
	S11	S3	0.569	S4	S10	0.778	S4	S7	0.619
	S4	S8	0.576	S7	S8	0.779	S7	S8	0.62
	S4	S10	0.58	S9	S10	0.79	S9	S7	0.638
	S1	S10	0.582	S7	S10	0.831	S6	S5	0.647
	S4	S3	-0.586	S4	S7	0.833	S9	S1	0.653
	S9	S1	0.598	S4	S6	0.841	S8	S10	0.654
	S4	S2	-0.6	S9	S8	0.846	S11	S1	0.667
	S11	S2	0.602	S9	S4	0.866	S9	S11	0.708
	S6	S8	0.618	S6	S8	0.888	S3	S2	0.712
	S9	S7	0.649	S7	S6	0.901	S1	S3	0.748
	S9	S10	0.678	S3	S2	0.92	S4	S10	0.825
	S4	S1	0.693	S9	S6	0.923	S7	S10	0.856
	S11	S4	-0.899	S9	S7	0.945			
	S3	S2	0.978						

Note: Spreads: S1) 3m LIBOR–OIS spread; S2) 3-m Aa Fin. CP–T-bill; S3) 3-m Asset-Backed CP–T-bill; S4) Aaa 1-y ARM–T-bill; S5) 5-y Interest Rate Swap–Treasury; S6) 5-y REFcorp–Treasury; S7) 5-y Aaa Private-Label CMBS–Treasury; S8) 10-y Off–On the Run–Treasury; S9) 20-y Moody's Baa–Aaa; S10) 20-y Junk Spread Corporate Bbb-Aa; S11) 30-y Freddie Mac Conventional Fixed Rate Mortgage–Treasury. Subperiods. Pre-crisis: 9/27/2002–7/27/2007; Crisis: 8/3/2007–/26/2009; Post-crisis: 7/3/2009–12/30/2011.

Table C2. Ng's Uniform Spacings Test of Zero Cross-Section Correlation (8 Spreads)

Sample Period	Pairs	% (S)	Positive Corr.	Negative Corr.	q=2 SVR	q=2 Prob.	q=4 SVR	q=4 Prob.	q=6 SVR	q=6 Prob.
Pre-Crisis	28	100.00	16	12	0.959	0.338	0.978	0.328	0.139	0.889
Crisis	28	100.00	22	6	0.478	0.632	0.213	0.831	0.402	0.688
Post-Crisis	28	100.00	23	5	**3.346**	0.001	**3.990**	0.000	**2.296**	0.022

First Split

Low Absolute Correlation Set

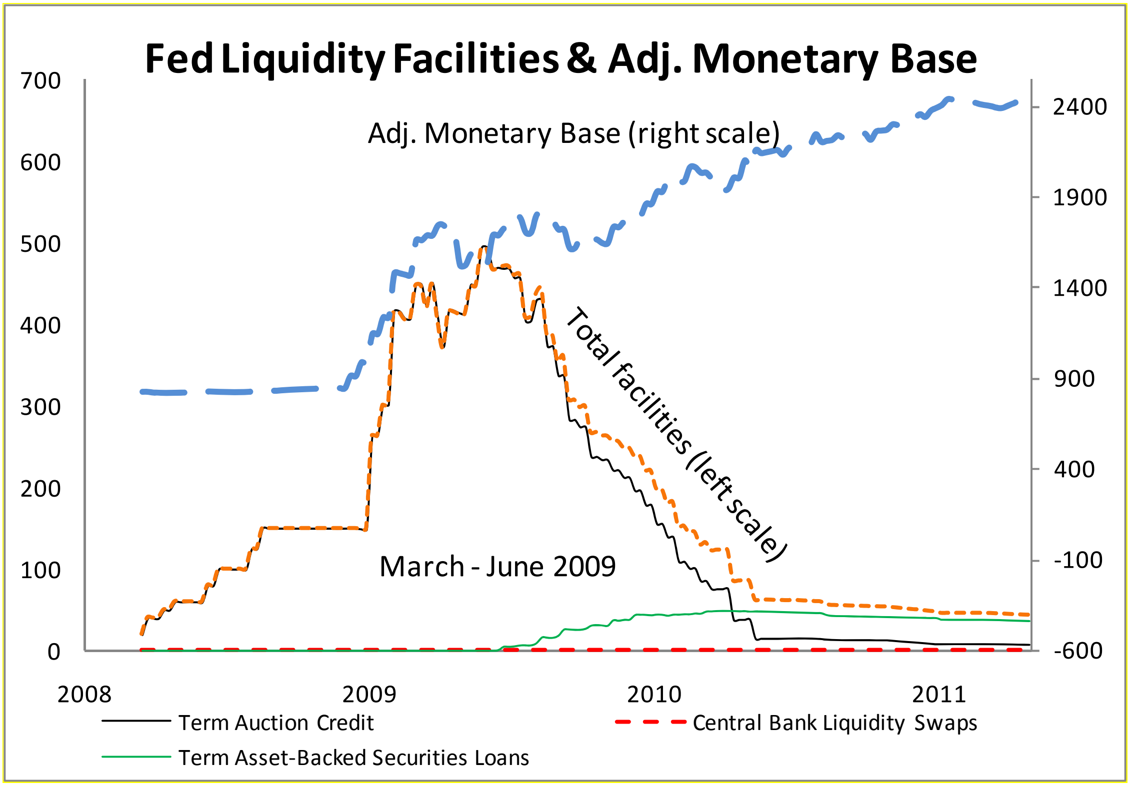
Sample Period	Pairs	% (S)	Positive Corr.	Negative Corr.	q=2 SVR	q=2 Prob.	q=4 SVR	q=4 Prob.	q=6 SVR	q=6 Prob.
Pre-Crisis	3	10.71	1	2	**-1.732**	0.083	-0.926	0.355	-0.701	0.484
Crisis	3	10.71	1	2	**-1.732**	0.083	-0.926	0.355	-0.701	0.484
Post-Crisis	4	14.29	2	2	-1.182	0.237	---	---	-0.809	0.418

High Absolute Correlation Set

Sample Period	Pairs	% (1-S)	Positive Corr.	Negative Corr.	q=2 SVR	q=2 Prob.	q=4 SVR	q=4 Prob.	q=6 SVR	q=6 Prob.
Pre-Crisis	25	89.29	15	10	-1.366	0.172	-1.264	0.206	-1.148	0.251
Crisis	25	89.29	21	4	1.274	0.203	**2.727**	0.006	**2.013**	0.044
Post-Crisis	34	85.71	21	3	0.909	0.363	-0.271	0.786	-0.452	0.651

Note: The table reports the results of spacings tests of zero cross-section correlation for 11 yield spreads. The parameter θ that partitions the N=55 absolute sample correlations into two groups (S, containing the smallest absolute correlations, and L, containing the largest absolute correlations) is estimated by maximum likelihood. The null of zero cross-section correlation within each group (including the original, full sample of 55 correlations) is tested using a standardized SVR test. SVR statistics in bold indicate rejection of the null hypothesis. Spreads. S1: 3-m LIBOR–OIS Spread; S3: 3-m Asset-Backed CP–T-bill; S4: Aaa 1Y ARM–T-bill; S6: 5-y REFcorp–Treasury; S7: 5-y Aaa Private Label CMBS–Treasury; S8: Off-On the Run 10-y Treasury Spread: S9; 20-y Moody's Baa-Aaa; S11: 30-y Freddie Mac Conventional Fixed Rate Mortgage–Treasury. Subperiods. Pre-Crisis: 09/27/2002–07/27/2007; Crisis: 08/03/2007–06/26/2009; Post-Crisis: 07/03/2009–12/30/2011.

Table C3. Quantitative Evolution of Federal Reserve Credit Facilities and Adjusted Monetary Base



Note: The figure plots the total amount (in billions of dollars) of the credit extended to the economy by the Fed through the Term Auction Facility (TAF), the bilateral currency swaps established with a number of central banks between 2007 and 2009, and the TALF. As a benchmark, and because it is directly affected by the securities (Treasury and mortgage-backed securities) purchases implemented by the Fed in 2008-10, the chart also plots the total adjusted monetary base in billions of dollars.

Table C4. Unit Root Tests on Yield Spread Series

The table reports the results from the application of two types of unit root tests on yield spread data over the full sample period, September 2002 to December 2011. The two unit root tests are the standard Augmented Dickey-Fuller (ADF) test (number of lags of spread changes in the test regression is selected by minimization of the BIC information criterion with a maximum number of lags equal to 12); and the nonparametric Phillips-Perron (PP) test, which controls for serial correlation when testing for a unit root. In both the ADF and PP tests, the only exogenous regressor in the test regression is a constant intercept tem. Boldfaced p-values indicate that the null of a unit root may be rejected with a p-value of 10% or lower.

	Weekly Obs.	Diff.	Augmented Dickey-Fuller Test			Phillips-Perron Test		
			ADF t-Statistic	P-value	BIC-based Lag Length	PP Adj. t-statistic	P-value	Band-width
3-month LIBOR-OIS	484	Level	-2.908	**0.045**	4	-2.974	**0.038**	11
		First-diff.	-13.133	**0.000**	3	-12.555	**0.000**	26
3-month Fin. Comm. Paper-Treasury	484	Level	-7.05	**0.000**	0	-6.542	**0.000**	13
		First-diff.	-39.604	**0.000**	0	-49.405	**0.000**	40
3-month Asset-Backed Comm. Paper-Treasury	484	Level	-3.961	**0.002**	4	-3.914	**0.002**	11
		First-diff.	-13.651	**0.000**	3	-23.473	**0.000**	19
1-Year Aaa Adj. Rate Mortgage Rate - Treasury	484	Level	-0.719	0.839	0	-0.910	0.785	10
		First-diff.	-21.364	**0.000**	0	-21.783	**0.000**	9
5-year Swap - Treasury	484	Level	-2.392	0.144	3	-5.350	**0.000**	9
		First-diff.	-19.524	**0.000**	2	-59.950	**0.000**	34
5-year RefCorp - Treaury	484	Level	-1.713	0.424	3	-2.960	**0.040**	5
		First-diff.	-17.934	**0.000**	2	-45.830	**0.000**	20
5-year Comm. MBS Rate-Treasury	484	Level	-2.282	**0.060**	9	-2.720	**0.071**	16
		First-diff.	-7.753	**0.000**	8	-37.001	**0.000**	15
10-year Off-On the Run Treasuries	484	Level	-7.663	**0.000**	4	-30.545	**0.000**	25
		First-diff.	-17.027	**0.000**	11	-213.48	**0.000**	134
20-year Aaa-Baa Moody's Default Spread	484	Level	-2.983	**0.037**	1	-3.211	**0.020**	20
		First-diff.	-25.162	**0.000**	0	-25.964	**0.000**	17
20-year Bb-Aa Moody's Junk Spread	484	Level	-2.560	**0.100**	0	-2.365	0.152	12
		First-diff.	-12.582	**0.000**	2	-20.239	**0.000**	11
30-year Fixed Rate Mortgage Rate-Treasury	484	Level	-3.144	**0.024**	0	-3.083	**0.044**	2
		First-diff.	-39.091	**0.000**	0	-39.101	**0.000**	3

Table C5. Quantile-Quantile Plots of the Transformed Absolute Correlations over Subperiods